Does Conservation Work in General Equilibrium?*

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Abstract

Deforestation and the subsequent use of deforested land for agricultural activities account for roughly 20% of the global CO2-equivalent emissions in the past two decades. Despite the global scope of the consequences of deforestation, public policies and private initiatives to reduce deforestation are often spatially targeted: they intensify environmental protection in specific ecosystems, making agricultural land scarcer. While potentially effective at a local level, their global effectiveness may be attenuated in general equilibrium, due to resulting increases in the demand for agricultural land in non-targeted areas, i.e. deforestation leakage. To quantify leakage, we build a quantitative spatial equilibrium model of the Brazilian economy where agricultural land is the output of a costly process of deforestation, firms produce goods that are differentially land-demanding, and there is costly trade and migration. Our main findings are that (i) targeting the regions with highest deforestation levels can be an effective tool to curb aggregate deforestation in Brazil, and (ii) leakage increases significantly when considering a longer time-horizon. After one year, 2-3% of the deforestation reductions are outdone by leakage. Simulating the model forward for 10 years, this number goes up to 10%. The relatively small leakage is driven by agricultural intensification, including more crop farming, increased worker and cattle density per pasture, and shifts of production towards more productive regions.

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1 Introduction

Tropical deforestation is among the human activities with the highest environmental impact. Forest clearing and the subsequent land use for agricultural activity are responsible for about one-fifth of global CO2-equivalent emissions over the past two decades. In addition to direct instantaneous carbon emissions, deforestation permanently destroys carbon sinks, causes the extinction of species, degrades native soil, alters weather patterns, and negatively impacts the livelihoods of millions ofdiscf people living in forest dwelling communities. Given its enormous environmental damage, combating deforestation is a key component of emission reduction pathways in the global fight to mitigate the effects of climate change, as established by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2019)[1]. Nevertheless, strategies to mitigate deforestation are excluded from major green finance mechanisms, such as the United Nations Clean Development Mechanism (CDM), due to concerns about leakage of locally targeted policies into untargeted areas, i.e. the reduction of deforestation in a specific area might be outdone by increases in deforestation elsewhere, undermining the global effects of local policies[2].

Since approximately three-quarters of global deforestation is driven by agriculture, quantifying the general equilibrium effects of anti-deforestation policies requires a model of how agriculture is redistributed across space in response to local policies. To that end, we build a quantitative model that explicitly embeds deforestation as an economic sector that supplies land as a factor of production for agriculture. Beyond the direct policy relevance of assessing the global efficiency of localised policies, this framework can guide the understanding of broader trade-offs in environmental policy (promoting conservation vs curtailing agricultural production), and the value of mitigating global externalities of localised deforestation activities[3].

Deforestation in Brazil

With over 5 million km^2 of rainforest area (MapBiomas Collection 6.0), Brazil accounts for about one third of all remaining rainforests and 13% of all forests in the planet, far more

[1]In its 2019 Special Report on Climate Change and Land, the IPCC mentions the word "deforestation" a total of 493 times, and states that *"Reducing deforestation and forest degradation lowers GHG emissions, with an estimated technical mitigation potential of 0.4–5.8 GtCO2/yr"*

[2]The UN defines deforestation leakage as *"The unexpected loss of anticipated carbon benefits due to the displacement of activities in the project area to areas outside the project, resulting in carbon emissions."*. In other words, locally targeted policies might not decrease overall deforestation, but rather displace it to untargeted areas.

[3]This framework could be used, for example, to implement a compensation policy for specific regions or for the country as a whole, a policy that has been suggested by a number of researchers and politicians as the only viable way to sustainably avoid deforestation (Brner and Wunder, 2008).

than any other country. It also accounts for a third of yearly tropical deforestation, with an average net yearly forest loss of about 20,000 km^2 between 1985 and 2020[4] (roughly equivalent to the size of Wales, or the American state of Connecticut). As such, outcomes of policies aimed at reducing deforestation in Brazil will have significant impact in the global forest coverage and, consequently, carbon emissions.

Deforestation has played an important role in the Brazilian economy over the past 35 years as an input for the country's agricultural sector, currently responsible for approximately one-quarter of the Brazilian GDP (CNA and CEPEA, 2023). Since 1985, the first year for which reliable high resolution satellite data on land use is available, total agricultural area has increased by more than 45%, or 840,000 km^2 (MapBiomas Collection 6.0), of which 92% were previously forests and 8% were previously tropical savannas. This activity is highly spatially concentrated along the so-called "arc of deforestation", in the fringe of the Amazonian forest, especially in the states of Pará, Mato Grosso and Rondônia. The large municipality of São Félix do Xingu, in the state of Pará, with a total area of around 84,000 km^2 (roughly the size of Austria), is an excellent illustrative example. In 1985, it had a forest cover of over 80,000 km^2, more than 95% of its total area, and agricultural activity occupied only 410 km^2 (0.5%). In 2021, it had just under 63,000 km^2 (under 75% of its area) of forest cover, and over 19,000 km^2 (well over 20%) of agricultural land, most of which pastures.

Over the past three decades, the Brazilian government has enacted a wide array of policies aimed at tackling deforestation. These policies include country-level actions, such as changes in the national legislation (e.g. Forest Code) or the use of satellite monitoring (SIVAM - from the 90s), but also localised policies aiming at protecting specific areas of the Brazilian territory. The latter group, which is the focus of this study, has typically been implemented either as increased enforcement in areas with particularly high deforestation, or as the designation of specific areas in the territory as conservation units or protected indigenous land. Such localised policies have been the subject of past evaluation which has generally found them to be successful in the targeted areas (Assunção and Rocha, 2019).

Typically, studies evaluating such policies use an event study approach to measure their effectiveness in the targeted regions vis-à-vis comparable non-targeted regions (Assunção and Rocha, 2019). However, this approach does not account for potential relocation of deforestation activities into non-targeted areas, which can significantly attenuate the effect of such policies on overall country-wide deforestation. To illustrate this idea, suppose that regions targeted by a certain policy see a decrease of 5,000 km^2 in their annual deforestation, whereas comparable non-targeted regions see an increase of 5,000 km^2 in annual deforestation

[4]The gross loss of primary forest has been higher, over 25,000 km^2 per year, but has been considerable forest regrowth.

rates – i.e. there is perfect relocation. A simple difference-in-differences analysis would suggest that the policy decreased deforestation by 10,000 km^2 when in fact it only changed where it occurred, and the net global effect is zero. This issue, referred to in the climate policy literature as leakage, is often discussed (Pfaff and Robalino, 2017) but rarely measured when evaluating specific anti-deforestation policies[5].

The Model

Our model considers a multi-region economy with two main sectors: agriculture and non-agriculture. The agricultural sector is further split into different types of crops and pastures that demand different amounts of land and labour as factors of production, whereas the non-agricultural sector has only labour as input. Crucially, we model deforestation as an intermediate sector which endogenously supplies land as a factor of production for agriculture. Each location differs in their sectoral productivity (agricultural, non-agricultural and deforestation), amenities and trade links. We allow workers to migrate between regions subject to frictions, and goods to be traded across regions subject to iceberg costs.

In the model, a local anti-deforestation policy is modelled as an exogenous negative shock to land supply in a targeted region. Leakage happens due to relocation of agricultural activity via the markets for goods and labour. In the goods market, a local decrease in supply of land will decrease the local supply of agricultural goods. Consumers then substitute these goods with non-agricultural goods, or with agricultural goods produced elsewhere, increasing demand for land in other regions, which creates leakage. Analogously, in the labour market, a decrease in supply of land will decrease the local demand for agricultural labour – workers will then partly change sectors, and partly migrate increasing the supply of agricultural labour elsewhere, which also creates leakage. The extent to which reductions in forest loss are outdone by leakage ultimately depends on the elasticity of demand for agricultural goods, and on the substitutability of agricultural land across space.

Literature and contribution

An increasingly widespread availability of satellite-image data has contributed to a growing wave of empirical research on the economics of deforestation (Balboni et al., 2023). This research has explored the key role of conservation policies, agricultural prices, trade, roads,

[5] It has become increasingly common to measure spillovers by looking at the changes in land use in the vicinity of protected areas, for example. While a valuable empirical exercise, it might not appropriately account for global spillovers, as the most suitable substitute for the land being protected may be in an entirely different part of the country - in this approach, the choice of which areas can be the subject of spillovers needs to be made *ex-ante* and is arbitrary.

property rights, and conflict, amongst others. We consider how our research relates first to those that take a reduced-form approach and then to those that build structural models and look at general equilibrium effects.

First, let us consider the broad literature evaluating the effectiveness of conservation policies (Burgess et al., 2019, 2012; Jayachandran et al., 2017; Szerman et al., 2022; Assunção and Rocha, 2019). We conceptualise these as tackling the "supply-side" of the market for new agricultural land. The main policies considered are: command-and-control place-based restrictions (the focus of this work), payments for ecosystem services (PES), taxes (often hypothetical) and tariffs. Existing evidence suggests that command-and-control policy instruments have played a crucial role in the slowdown of deforestation in Brazil. Assunção and Rocha (2019) focuses on the Priority List of municipalities and shows reductions of around 50% in the treated municipalities. Recently, the empirical micro literature has started to pay more attention to potential spillovers from conservation policies. Pfaff and Robalino (2017) summarise the theory and evidence on the spillovers of conservation programs which, at the time, lacked any structural quantitative analysis of spillovers due to general equilibrium effects. Instead, it looked at spillovers to neighbouring areas outside conservation zones. This has the advantage of measuring all the different types of spillovers from conservation policies. There may be positive enforcement spillovers, as well as negative spillovers, i.e leakage. However, identification of spillovers in reduced-form requires the assumption that they decay with distance to the protected areas and that places further away are valid controls. Fuller et al. (2019) systematically review the evidence on deforestation leakage from Protected Areas and find evidence of leakage in 12% of the protected areas where there is evidence of deforestation reduction, and the magnitude of its incidence seem to be highly context dependent. Alix-Garcia et al. (2012) investigate a Mexican PES scheme and estimate that leakage undoes about 4% of the deforestation reductions. Robalino et al. (2017) analyse the heterogeneity of the spillovers of new national parks in Costa Rica by distances to roads and distances to park entrances. They find large and statistically significant leakage close to roads, which increases access to markets, but far from park entrances, which increases access to tourism, consistent with their theory. They also find that parks facing greater threats of deforestation show greater leakage. Another strand of reduced-form empirical literature has explored the response of deforestation to changes in demand for new agricultural land, driven by commodity prices, rural credit access, and market access. These are important contributions and inspiration for our work as they highlight how deforestation is a process that is intimately linked to the agricultural economy (Assunção et al., 2015; Berman et al., 2023).

Second, we contribute to the literature on trade and the environment that relies on structural modeling. The seminal work of Copeland and Taylor (2004) builds a theoretical trade model that formalises the ambiguous effects of trade on environmental conservation. Quantitative spatial models have proven useful to model how comparative advantage in agricultural activities shapes the spatial distribution of different land uses (Cui, 2020; Pellegrina and Sotelo, 2021). More recently, the IO and trade literature has started to look at deforestation explicitly through structural models (Souza-Rodrigues, 2018; Hsiao, 2021; Domiguez-Iino, 2021; Araujo et al., 2020; Tsuda et al., 2023). We contribute to this literature by adding labour and migration to general equilibrium models of land use change, and by explicitly linking land use changes with patterns of economic growth and structural change in space (Eckert and Peters, 2022; Farrokhi and Pellegrina, 2020; Bustos et al., 2016; Herrendorf et al., 2014; Boppart, 2014). We do this by extending the spatial equilibrium model of structural change proposed by Eckert and Peters (2022) by (i) adding a deforestation sector that endogenously produces new agricultural land, and (ii) considering different agricultural sectors that can have heterogeneous shares of land and labour as in Farrokhi and Pellegrina (2020).

In this paper, we aim to quantify one specific source of conservation spillovers: the general equilibrium effects caused by local reductions in new agricultural land where the conservation policy is implemented, leading to increased demand for agricultural land elsewhere, and hence potentially more deforestation. By looking at locally targeted reductions in deforestation in a general equilibrium framework we can make predictions about the likely size of anti-deforestation policies' leakage and its spatial distribution. This can help assess whether it is actually likely to happen only nearby or if there are more distant regions likely to be affected by leakage, perhaps because of market access or greater agricultural suitability. Our modelling approach can be used both to inform targeting decisions in future conservation policy and to correct biases in retrospective reduced-form policy evaluation.

2 Data

The data used in this paper is available at different levels of spatial granularity. For the reduced-form analysis, we overlay the extension of the Brazilian territory with a hexagonal grid with 10 km width, and we take each hexagonal grid cell to be the unit of analysis. The whole country of Brazil has 100,173 10-km-wide hexagons, each with an area of 779.42 km^2. For comparison, the average municipality in Brazil has an area of 1,571 km^2 and the average municipality in the Legal Amazon[6], where the population is much more sparse, has

[6] The Legal Amazon is the region of Brazil comprised by the states of Acre, Amapá, Amazonas, Maranhão, Mato Grosso, Pará, Rondônia, Roraima, and Tocantins.

an area of 6,369 km^2. This is done for two reasons. First, in the case of the analysis of the Protected Areas, their boundaries do not coincide with the boundaries of municipalities, and this requires either looking at a continuous treatment, the fraction of municipality protected, or choosing an arbitrary threshold after which regions would be considered treated, introducing measurement error. Second, grid cells are a more comparable units of analysis and increase the statistical power of the analysis. Grid-cells all have the same area whereas the municipalities range from 3.8 km^2 to 161,104 km^2 and the 90th percentile is 23 times the 10th percentile. Thus, for the evaluation of the Priority List municipalities, we will also look at the grid cell level as a robustness check.

For the quantitative model, we need a unit for which there is economic and demographic data as well. The lowest geographical level at which this can be obtained is the municipality level. We choose instead the micro-region level, of which there are 558 in Brazil. At a practical level, this reduces the computational requirements of this analysis significantly. It also has an advantage in terms of interpretation, which is that the micro-regions correspond more closely to local labour markets or commuting zones. The micro-region corresponding to the greater Rio de Janeiro, for example, is comprised of 16 municipalities - one of which is the municipality of Rio de Janeiro. Micro-regions are on average comprised of 10 municipalities, though this ranges from 1 to 41. The median micro-region has 8 municipalities. In the Legal Amazon, since municipalities are larger, each micro-region is on average comprised of 7.5 municipalities, the median is 6, and they range from 2 to 25. Another attractive feature of micro-regions when compared to municipalities is that there is less dispersion in the distribution of their area for Amazonian municipalities. The interquartile ratio of surface areas of municipalities in the Legal Amazon is 6.7, compared to 3.2 for micro-regions.

2.1 Land use and land use change data

Data on land use and land use change comes from the MapBiomas project, a multi-institution collaborative initiative that processes satellite images into publicly available datasets on land use for the Brazilian territory. The first dataset used contains land use data for Brazil between 1985 and 2020 at 30 m resolution. Each 30 m pixel in this dataset belongs to a land use category.

Land use

The original data have 28 land use categories. For most of the analysis, we disregard the distinction between (i) types of forest, (ii) types of other non-forest natural ecosystems, (iii) types of perennial crops, (iv) types of temporary crops, and (v) types of non-agricultural and non-vegetated areas such as urban, mining, and bodies of water. For the reduced-form analysis and the descriptive statistics, we will aggregate these data at the hexagon level, so that for each hexagon we observe the area it contains in each of these categories for every year. For the quantification of the model, the data is aggregated at the micro-region level.

Land use change

When aggregating at the hexagon-year level, however, some information is lost regarding the details of the land use changes that occurred. If, for example, a 10 km^2 region of a hexagon is deforested and, simultaneously, a 15 km^2 area is reforested, we would only be able to see the net change, that is a 5 km^2 increase in forest area. In order to overcome this challenge, we use MapBiomas' Land Use Change product, which, for every 30 m pixel for 1988-2019, identifies several types of deforestation and several types of reforestation. We will focus on three main types of transitions: (i) loss of primary vegetation to anthropic use, (ii) loss of secondary vegetation to anthropic use, (iii) regrowth, that is from anthropic use to secondary vegetation. It is worth noting, however, that everything that has been forest since 1985 is classified as primary vegetation, and all vegetation in pixels that have been classified as anthropic from two consecutive periods in the past (starting in 1985) is classified as secondary.

2.2 Geographic data

Administrative boundaries

Data on the administrative boundaries of municipalities, micro-regions and states comes from the Brazilian Institute of Geography and Statistics (IBGE) and is publicly available. Brazil is a federation comprised of 27 federative units: 26 states and 1 federal district, the capital city of Brasilia. The current division in states has remained the same since 1988. States are in turn divided into municipalities. As of 2023, there are 5,570 municipalities. For the quantitative model we will select a higher scale of aggregation, the micro-region, of which there are 558 including Brasilia, which more closely resemble commuting zones.

Conservation Policy data

The geo-coded information on Indigenous Territories comes from the website of the National Foundation of Indigenous Peoples (FUNAI)[7]. The FUNAI also provides information on the

[7] https://www.gov.br/funai/pt-br/atuacao/terras-indigenas/geoprocessamento-e-mapas

year in which they have undergone the five stages of approval (study, delimitation, declaration, homologation, and regularization). We consider the homologation as their year of creation, as this is the stage of judicial approval officially recognising the territory as an indigenous land.

Geo-coded information on the Conservation Units comes from the website of the Ministry of the Environment[8]. They also contain data on the year of creation of the various conservation units.

Environmental data

I gather publicly available data on temperature, precipitation, soil moisture, and the carbon density of ecosystems from a variety of sources. Temperature data comes from TerraClimate. The data gathered is the minimum and maximum monthly temperature at 4638.3 m resolution for years 1985-2019. Precipitation data comes from ERA5. The data gathered is the monthly aggregate precipitation in mm at 11132 m resolution for years 2000-2019. Soil moisture data also comes from TerraClimate. It is measured in monthly mm and is derived using a one-dimensional soil water balance model. The spatial resolution and time period are the same as for temperature. Above and Below Ground Biomass Carbon Density comes from the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) carbon biomass dataset. This dataset estimates a snapshot of biomass carbon density for 2010. We use these data, alongside land use data for 2010, in order to assign an average carbon density to the natural ecosystems in different micro-regions and that way approximate the carbon emissions under different simulated scenarios.

2.3 Economic data

This paper uses economic data for four purposes. First, as ancillary outcomes of the reduced-form analysis of Priority List municipalities[9]. Second, to calibrate some of the structural parameters of the model in 5.1. Third, to structurally estimate the productivities at the micro-region-year level in 5.2. And fourth, to validate the model estimation by checking the correlation of model-derived moments and unmatched moments in D.6. The precise way in which the data is used will be described in the relevant sections in greater detail. All price data is deflated to 1994 Reais.

[8]https://antigo.mma.gov.br/areas-protegidas/cadastro-nacional-de-ucs/dados-georreferenciados.html

[9]Since the most granular level at which this is observed is the municipality level, this analysis is done at the municipality instead of the grid-cell level.

Agricultural data

Our main sources of agricultural data are: the 2006 Agricultural Census, the Municipal Survey on Agricultural Production (PAM) for 2000-2019, and the Municipal Survey on Livestock Production (PPM). The variables of interest from the agricultural census, at the municipality level and for each agricultural activity (pastures, temporary crops, and permanent crops), are: (i) agricultural area, (ii) number of workers employed in that activity, and (iii) revenues. From the PAM we have, at the crop-municipality-year level, estimates of: (i) area planted, (ii) production (kg), (iii) revenues. The PPM, for livestock, does not provide area not revenues, but it has an estimate of the number of cows per year per municipality which we combine with other data to estimate revenues and intensity of production.

The main agricultural data needed for the model is a yearly panel of the revenues from each of the three primary agricultural activities modelled. The Municipal Survey on Agricultural Production (PAM), provides yearly estimates of the revenues of 71 different crops. For the model, we aggregate crops into two categories: temporary and permanent, in a way that is consistent with their classification in the agricultural census. These estimates yield very similar values to those in the agricultural census in 2006.Instead of relying on the PAM alone, we construct an region-level index of the PAM revenues that equals one in the 2006 and multiply them by the 2006 Agricultural Census data as follows

$$\widehat{Reveue}^{k}_{rt} = Revenue^{k,AgCensus}_{r2006} \times \frac{Revenue^{k,PAM}_{rt}}{Revenue^{k,PAM}_{r2006}}$$

for each $k \in \{\text{permanent crops}, \text{temporary crops}\}$. This ensures that we use the cross-sectional variation in levels coming from the agricultural census, which is likely to be more accurate, and then use the PAM to estimate the relative yearly variation in each municipality.

No data on yearly revenues from cattle ranching at the municipality level exists for Brazil, so we leverage cross-sectional data on other sources that cover the dimensions governing yearly revenue changes: the number of cows, the weight of each cow, and the price of beef. We obtain yearly estimates of the number of cows in each municipality from the Municipal Survey on Livestock Production (PPM). We obtain data on yearly national variation in the price of beef in each year from a daily time series curated by the School of Agricultural Studies of the University of São Paulo[10]. We obtain yearly state-level data on the average weight of slaughtered cows from the national statistical office's Quarerly Survey of Salughtered Animals. Given the average age of a cow at the time of slaughter is 3 years, we estimate yearly cattle revenues by multiplying the 3-year lagged change in weight, number of cows

[10] Available for public consultation at: https://www.cepea.esalq.usp.br/br/indicador/boi-gordo.aspx

and price of beef by the 2006 revenue data from the Agricultural Census[11], so that for region r in state $s(r)$:

$$\widehat{Reveue}_{rt}^{\text{pasture}} = Revenue_{r2006}^{k,AgCensus} \times \frac{p_t^{\text{beef}}}{p_{2006}^{\text{beef}}} \times \frac{kg/cow_{s(r)t-3}}{kg/cow_{s(r)2003}} \times \frac{\#\, cows_{rt-3}^{PPM}}{\#\, cows_{r2003}^{PPM}}$$

Other economic data

For the validation of the model and as ancillary outcomes of the municipality-level reduced-form analysis of the Priority List municipalities, we use data on municipal GDP and wages.

I leverage data on Gross Domestic Product and gross value added by major sector (agriculture, manufacturing, services, and public administration) at the municipality level for the years 2002-2019. These data are estimated by the Brazilian Institute of Geography and Statistics (IBGE) in partnership with State Statistical Organisations, State Government Departments, and Free Trade Zones.

Wage data comes from the population census of 2000 and 2010. In both of these individuals are asked to report their current monthly income. We aggregate these data so that we have, for each micro-region and each year, the average wage in agriculture and the average wage in non-agriculture. These data are also used in order to calibrate the share of labour in agricultural production in the model.

Internal trade

Data on interstate trade flows comes for 1999 comes from (de Vasconcelos, 2001), as cited by Morten and Oliveira (2018). This is a matrix of the inter-state trade in goods and services of Brazil. These data come from administrative records collected by the author from each state's office. At the time the records were not centralised nor digitised and it is likely that there were more gaps and inconsistencies. For 2017, the data comes from the National Council of Fiscal Policy (CONFAZ), which relies on data from the Electronic Invoice (NF-E) to establish the interstate commercial balance. The NF-E contains details of goods departure, including its destination and value, as well as information about the entry of merchandise. CONFAZ aggregates these data to calculate interstate exports and imports. Given potentially large gaps in trade flow records (in 1999, five states, mostly Amazonian, did not have any records of inter-state trade) we use these data to estimate a distance-elasticity of trade rather than to match observed trade flows. Moreover, this analysis is at the micro-region level, not at

[11]This extrapolation over time requires the assumption that the yearly changes in the price of beef can be considered as constant across all municipalities, and that yearly changes on average slaughtered weight can be considered constant across all municipalities within a given state.

the state level, so we will use the state-level-estimated distance elasticity of trade costs to approximate the iceberg trade costs that decays with distance. More details can be found in subsection D.4.

Household expenditures

Finally, we use the 2017-2018 Household Expenditure Survey (POF) to calibrate the preference parameter that governs the non-homotheticity in individual utility. This survey contains individual-level data on incomes and itemised expenditures which are used to see the correlation between individual income levels and the share of their expenditure that goes to food. We use household expenditure shares on food items as a proxy for consumption of agricultural goods.

2.4 Demographic data

Data on micro-region level labour markets comes from 10% samples of the 2000 and 2010 National Census, which is representative at the municipal level (smaller than the micro-region), made publicly available by IBGE. For each municipality, we compute the share of individuals who report working in the agricultural sector, as well as the average municipal earnings for agricultural and non-agricultural activities. We get the number of workers in agricultural and non agriculture for both of these years and then, for each micro-region, we interpolate and extrapolate these values linearly to approximate their time series from 2003 to 2019. Given the static nature of the equilibrium concept, it is not too important to accurately measure relative yearly changes in population and labour shares, but to get the levels right. Therefore, we think that the errors introduced by this approximation are unlikely to change the main results. We also use the 2010 census to obtain information on internal migration, as respondents are also asked to report in which municipality they lived 5 years prior to data collection.

3 Local Effects of Targeted Conservation

Existing research suggests that Brazil's approach to tackling deforestation over the first two decades of the 21st century has been successful in reducing country level deforestation, (Burgess et al., 2019; Assunção et al., 2015) . During this period, a vast array of policies were implemented by the federal government. Some of these are "blanket-level" policies affecting the entire Brazilian territory, such as changes in laws increasing legal limits for deforestation in private land (DOU, 2012) and the adoption of a unified *Action Plan for the*

Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). Others, however, were locally targeted policies, which raises the concerns of possible leakage: has the forest loss avoided in these areas simply moved somewhere else?

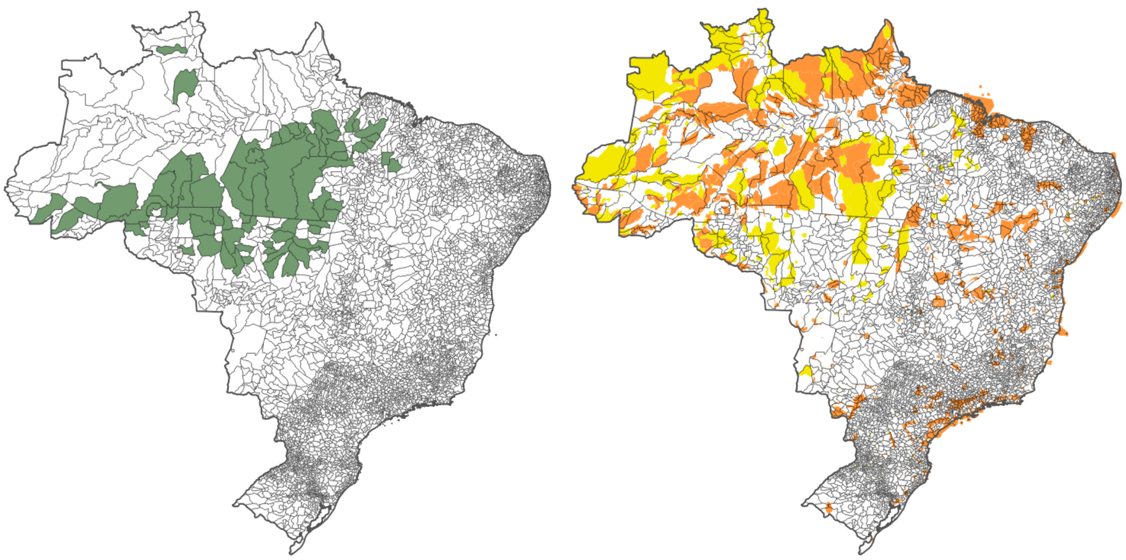
Among the local anti-deforestation policies enacted by the Brazilian government, two have been especially prominent. The first is the establishment of "Priority Municipalities" policy, enacted by the Brazilian government in 2007 (DOU, 2007). A set of municipalities in the Amazon region where deforestation rates were among the highest in the country were selected to be subject to extra enforcement actions. In a first round, 36 municipalities accounting for around 45% of the previous year's deforestation were included in the priority list, which has been updated on a yearly basis ever since. Selected municipalities were subject to increased law enforcement activities such as fines, embargoes on private farms, political agreements with local leaders, and credit incentives from the federal government. After the start of the policy, yearly deforestation in targeted areas significantly decreased (Assunção and Rocha, 2019). The second prominent example of local conservation policies is the continuous establishment by the Brazilian Government of specific areas where deforestation is completely banned. Such areas are established either for wildlife and biodiversity conservation – the so called Unidades de Conservação (Conservation Units), or for preservation of land that has been traditionally inhabited by native indigenous people – the so called Territórios Indígenas (Indigenous Territories). These policies began with the country's return to democracy in 1985 and, as of 2022, a total area of approximately 3,500 km^2 has been granted one of these two status. Due to their practical similarities, both types of policies will henceforth be referred to as Protected Areas. Unlike the Priority Municipalities policy, Protected Areas typically have high forest coverage and little deforestation, and the goal is to conserve the natural biome rather than to crack down on existing degradation.

Before turning to a quantitative analysis of leakage in place-based policies, it is important to discuss the reasons why, given the local effectiveness of targeted policies, one does not simply extend these policies to cover the entire country which would, by construction, end deforestation (and, trivially, leakage) altogether. Firstly, the enforcement of conservation policies is costly for public funds – research estimates that, in order to place 80% of the Brazilian Amazon under some form of currently existing policy, the federal government would need to spend at least 1.7 Billion USD per year (da Silva et al., 2022). Secondly, from a social welfare perspective, the conversion of forested land into agriculture generates private profits, which could result in a non-zero optimal level of deforestation from the perspective of Brazil. Thirdly, and related to the private optimal argument, there is a political cost of restricting deforestation activities, since the proceeds of those are often captured by local political elites. Fourthly, from a public revenues perspective, modern agriculture that results from forest removal is more easily measured and, consequently, taxed, than alternative sustainable economic activities

Reduced-form evidence from studies evaluating the effects of place-based conservation policies in Brazil suggest that they have been effective in decreasing deforestation in targeted areas. However, in order to capture the true effect of a local policy relative to a counterfactual in which this policy was never implemented, reduced-form methods rely heavily on the stable unit treatment value assumption (SUTVA) - i.e. absent treatment, non-treated areas would have behaved exactly as they did in the presence of treatment elsewhere. In the case of a conservation policy that can be subject to leakage, this assumption might not hold, as shown next.

3.1 Descriptives

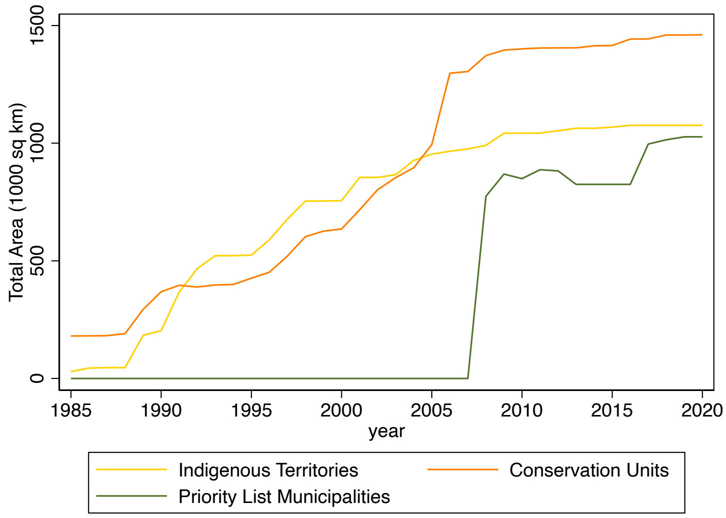
Figure 1: Spatial distribution of Priority List municipalities (green), Conservation Units (orange), and Indigenous Territories (yellow) as of 2021.



Note: This figure illustrates the spatial targeting of the three relevant types of protected areas implemented by the Brazilian government over the past decades. The left panel shows, in green, the municipalities that have been added to the Priority List since its start in 2008. The right panel shows the location of protected areas (which do not necessarily coincide with municipal borders) according to its type: orange areas are Conservation Units, yellow areas are demarcated Indigenous Territories

Figures 1 and 2 illustrate the evolution of place-based anti-deforestation policies in Brazil between 1985 and 2020. From Figure 1, we can see that both policies are largely focussed on areas in Amazonian region. The Priority List (in green) targets exclusively municipalities within the Brazilian Legal Amazon, most of which located in the so called "deforestation arc"

Figure 2: Evolution of spatially targeted conservation policies



Note: This figure illustrates the evolution over time of the total area under different types of locally targeted policies by the Brazilian government. The yellow line represents the total area of demarcated Indigenous Territories, the orange line represents the total area under Conservation Units, and the green line represents the total area of all municipalities included in the Priority List policy.

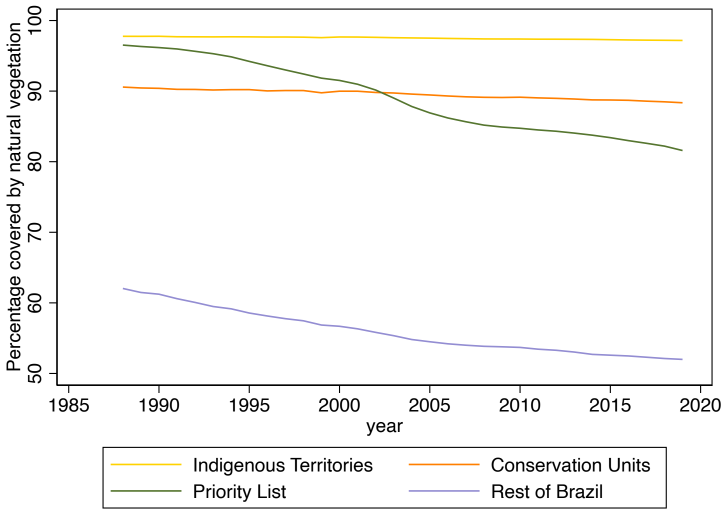
covering the south of the states of Amazonas and Pará and the north of the state of Mato Grosso. Although the Protected Areas are somewhat more spread across the country[12], they are still spatially concentrated in the Amazon biome, north of the municipalities in the Priority List, in areas with more untouched forest cover. In Figure 2, we can see the temporal evolution of these policies. Protected areas have been gradually established since the country's redemocratisation in 1985, whereas the Priority List policy was created in 2007, with most municipalities being added to the list in that same year.

Figure 3 below illustrates trends in forest change in Brazil according to their status as protected areas in 2020: indigenous territories, conservation units, and the rest of country. It is clear that, between 1985 and 2020, the bulk of forest loss happened outside protected areas. Throughout the period, forest cover in indigenous territories and protected areas have remained above 90% and 80% respectively, compared to those outside of them, which have gone from above 60% to under 50%.

However, this fact alone is not convincing evidence that they have worked as an effective halt on deforestation. The first concern with this simple comparison is the endogeneity of their placement - this is often referred to in policy circles as the question of "additionality". The second concern when evaluating the effectiveness of any local conservation policy is the

[12] Mainly due to territories historically occupied by indigenous peoples in the Northeast and Southeast regions

Figure 3: Area covered in natural vegetation under different conservation policies



Note: This figure illustrates the evolution over time of the territorial coverage in natural vegetation, as a share of total area, for regions under the different types of locally targeted policies implemented the Brazilian government. The yellow line represents the evolution of natural vegetation coverage in Indigenous Territories, the orange line represents represents the evolution of natural vegetation coverage in Conservation Units, and the green line represents the eevolution of natural vegetation cover in municipalities from the Priority List.

possible presence of spillover effects - in particular the question of "leakage".

Regarding endogeneity, the bias could be positive or negative. These territories may have been established in places without good soils for agriculture, far from roads and markets, or with geographic conditions that make them harder to deforest. But it could also go the opposite way, if environmental agencies respond to environmental threats by establishing protected areas and indigenous peoples decide to formalise protection as a reaction to settlers arriving and cutting down the forests in their land. It could go one way in places where the local politicians and bureaucrats are more aligned with the interests of agricultural businesses, and the other way where they are operating with the goal of stopping deforestation. In order to evaluate the effectiveness of the establishment of protected areas and indigenous territories in halting deforestation, we exploit their staggered establishment and look at places near their borders with a regression discontinuity design.

Most of the area under indigenous territories and protected areas has been assigned after 1985, which is when our land use data, taken begins. The graph below shows how the area under each of those property right regimes has changed over time.

The blacklist started in 2008. It is a subset of municipalities in the Legal Amazon that were chosen for their strategic importance in halting deforestation. The total deforestation levels the five years before are good predictors of blacklist status, although they do not seem to exactly determine blacklisting. Figure 2 illustrates how the blacklist has changed over time. In 2008, 36 municipalities were added to the list, covering a total area of approximately 800,000 square kilometers. Since then, the total number of blacklisted municipalities has not changed vary much, remaining around 40. The total area has increased to around 1,000,000 square kilometers. Some municipalities have entered and some have exited the blacklist. Upon exit, previously blacklisted municipalities acquire the status of "monitored". Since 2008, 20 municipalities have exited the blacklist and 3 of those have returned. There have been 2 periods of significant change in the blacklist. First, the period 2008-2012, with most of the action concentrated in 2008. Second, the period 2017-2020, with most of the action concentrated in 2017, when 9 municipalities covering over 200,000 square kilometers were added. The second period reflects a shift of deforestation further north, towards the Amazon river.

3.2 Effects of the Priority List

3.2.1 Econometric specification

To evaluate the effectiveness of placing municipalities in a Priority List, our preferred approach is synthetic differences in differences using as unit of analysis the municipality (Arkhangelsky et al., 2021). The main regression equation is

$$\text{(log) Forest Loss}_{mt} = \delta_t + \gamma_m + \beta \text{Priority}_{mt} + \epsilon_{mt} \tag{1}$$

and the dynamic version with different coefficients for different years relative to treatment, or event study, is

$$\text{(log) Forest Loss}_{mt} = \delta_t + \gamma_m + \sum_{\tau=-N_L}^{N_F} \beta_\tau \text{Priority}_{mt-\tau} + \epsilon_{mt} \tag{2}$$

where (log) Forest Loss_{mt} is the logarithm of the loss of natural vegetation observed in municipality m at year t, δ_t are year fixed effects, γ_m are municipality fixed effects, $\text{Priority}_{m,t-\tau}$ is a dummy variable equal to one if municipality m has been added to the Priority List exactly τ years ago, and β_τ are the coefficients of interest. we consider forest loss data between years 1995 and 2019.

Parallel trends

The validity of the event study approach relies on the assumption of parallel trends, i.e., treated and untreated (or not-yet-treated) municipalities followed parallel trends in deforestation rates in the years leading up to their treatment year, which implies $\beta_\tau = 0 \; \forall \; \tau \; \in [-N_L, 0)$. Given that the Priority List policy was explicitly targeted at municipalities considered "deforestation hotspots", treated municipalities followed different trends by design. The synthetic difference-in-differences model employed relaxes the parallel trends assumption and weights observations so that pre-periods exhibit parallel trends. The assumption is therefore that parallel pre-trends imply counterfactual trends after the implementation of the policy. The method used also adjusts for the problems arising from staggered adoption so that already treated units are never used as controls for units treated in later years. It also weights observations so that the parallel trends assumption is closer to being satisfied[13].

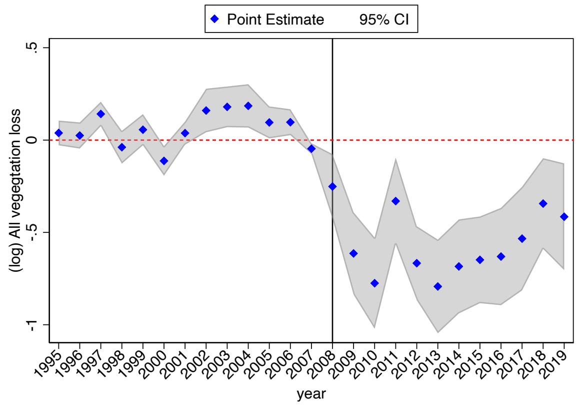
3.2.2 Results

Table 1 shows the average effects of the treatment effect on four main outcomes variables: (i) all loss of natural vegetation, (i) primary vegetation loss, (iii) secondary vegetation loss, and (iv) secondary vegetation gain or forest regrowth. These results come from looking at the Legal Amazon, where municipalities are more comparable to Priority List municipalities, and looking at all Priority List cohorts. Figure 4 below shows a visual representation of the event study estimates. For clarity of exposition, the event study restricts the sample to those municipalities that are treated in 2008 or those that are never treated. Panel (a) show the effects on the logarithm of the total loss of area in natural vegetation in the municipality. This is a sum of the loss of primary vegetation and the loss of secondary vegetation. The effects on the (log) primary vegetation loss and the (log) secondary vegetation loss are shown in panels (b) and (c) respectively. While panel (d) shows the effects on the (log) regrowth of secondary vegetation.

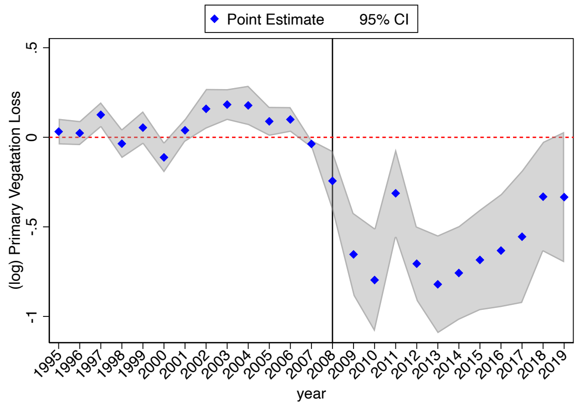
From Table 1, it can be seen that there is a large and statistically significant decrease in total forest loss of 0.44 log points, or 35%. This is the same as the observed reduction in primary vegetation loss, which is the vast majority of the deforestation observed. Secondary vegetation loss, on the other hand, went up by 17%, which is partially explained by the fact that the gains in secondary vegetation also went up, by 23%, so there is more forest classified as secondary available to cut down. In terms of the timing of the effects, there seems to be a large instantaneous decrease of around 50% in the first couple of years, gradually disappearing over the years. This is consistent with the change of administration towards the governments of Temer in 2016 and Bolsonaro in 2019, who openly declared their intention to reverse Lula and Rousseff's environmental policies and reduce the budget allocated to environmental agencies. The positive effects on forest regrowth also seem to disappear completely by 2019

[13]This is implemented using the sdid command in Stata developed by Clarke et al. (2023). Standard errors are generated with the bootstrap method with 50 repetitions and they are clustered at the municipality level.

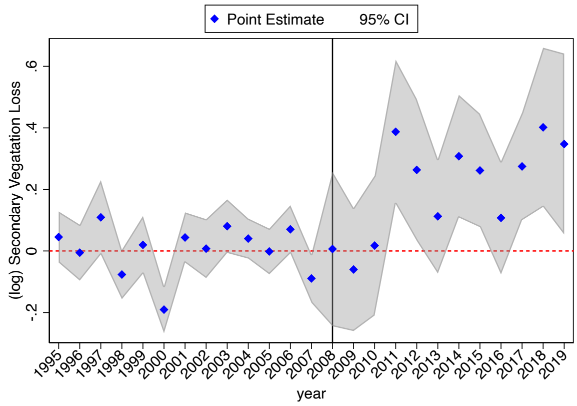
Figure 4: Dynamic effects of Priority List on Forest Cover Changes



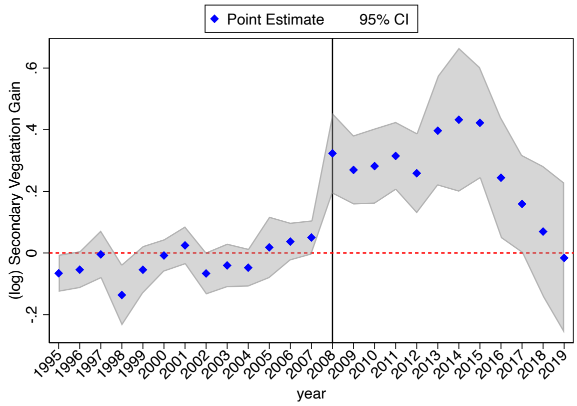
(a) (log) All loss of natural vegetation



(b) (log) Loss of primary vegetation



(c) (log) Loss of secondary vegetation



(d) (log) Gain of secondary vegetation

Note: This figure shows the municipality-year-level event study of the synthetic differences in differences regression of deforestation and reforestation outcomes (specifically: total loss of natural vegetation, loss of primary natural vegetation, loss of secondary vegetation, and gain of secondary vegetation) in logarithms on the onset of the Priority List in 2008. Since treatment is staggered, we restrict attention to the municipalities that join the Priority List in 2008 and those that never join as a pure control group. We only include municipalities in the Brazilian Legal Amazon, as they are more likely to resemble Priority List municipalities. Standard errors are calculated via bootstrap with 50 repetitions. In the regression results in table 1 we include municipalities that enter the list in other years and rely on Clarke et al. (2023), which does not use already-treated units as controls.

Table 1: Synthetic differences in differences (all outcomes in logs)

	Nat. veg. loss	Primary loss	Secondary loss	Regrowth
	(1)	(2)	(3)	(4)
Priority List	-0.445***	-0.443***	0.161***	0.210***
	(0.060)	(0.074)	(0.058)	(0.046)
Observations	19,575	19,375	17,025	19,375

Note: This table shows the results of the municipality-year-level the synthetic differences in differences regression of deforestation and reforestation outcomes (specifically: total loss of natural vegetation, loss of primary natural vegetation, loss of secondary vegetation, and gain of secondary vegetation) in logarithms on the onset of the Priority List. We only include municipalities in the Brazilian Legal Amazon, as they are more likely to resemble Priority List municipalities. Municipalities are dropped whenever there is any year in which the outcome is missing, which occurs in years with zero forest loss or regrowth. Standard errors, in parenthesis, are calculated via bootstrap with 50 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

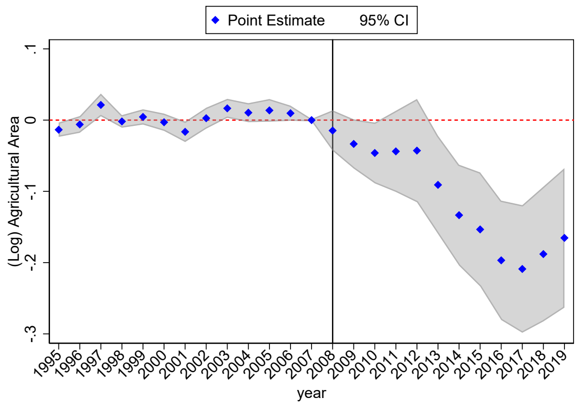
(Burgess et al., 2019).

Effects on other outcomes. We look at other agricultural outcomes in order to understand the relationship of the Priority List to the local agricultural economy more broadly.

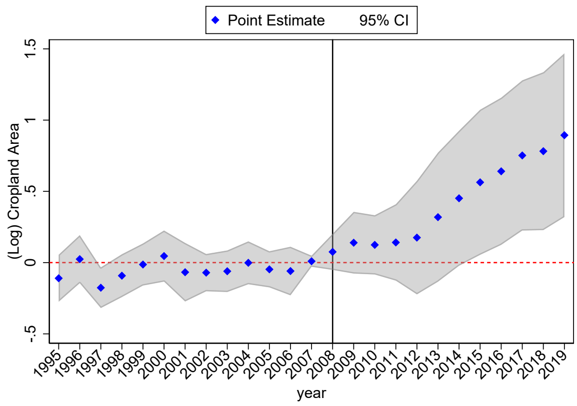
This is informative of the mechanisms via which deforestation is reduced. In particular, we find that deforestation is reduced by switching towards less land intensive activities. There is a persistent decrease in the area in pastures while there is an persistent increase in the total area in crops. There is not only an increase in the share of area in crops in the municipality, which we might expect if deforestation was simply halted and no other changes took place, since deforestation is mostly a conversion of forests to pastures. The increase is in the total area in crops. That is, although there is less agricultural area, there are more crops. Surprisingly, but consistently with the land use facts, municipalities that get added to the Priority List see an increase in their agricultural value added as measured in the Regional Accounting system. This seems to be primarily due to three phenomena: (1) a shift away from pasture towards crops (especially soy and maize) as seen in Figure 5, (2) an increase in the yields of some crops, and (3) an increase in the number of cattle heads per area in pasture.

Beyond informing how deforestation is reduced, these results help make sense of the effects of restriction in the supply of agricultural land on a wider set of economic decisions, which is informative of their general equilibrium effects. As will be shown in section 6, conservation policies lead to increases in the area in crops and to intensification in all agricultural activities. In this model, the only margin for such intensification is more labour per hectare. With higher frequency data on agricultural inputs, future research could assess empirically the margins along which the intensification of production occurs.

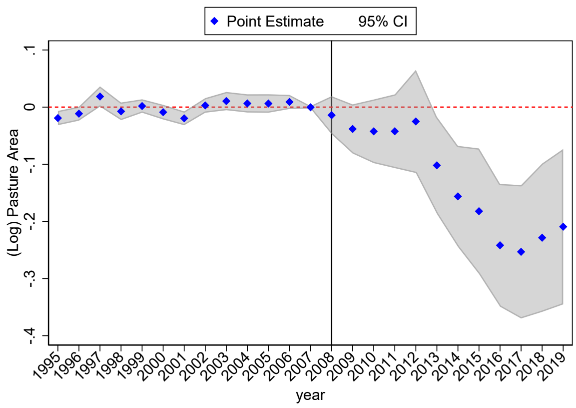
Figure 5: Dynamic effects of Priority List on Agricultural Land Use Changes



(a) (log) Agricultural Area



(b) (log) Cropland Area



(c) (log) Pasture Area

Note: This figure shows the municipality-year-level event study of the synthetic differences in differences regression of agricultural area stocks (specifically: total agricultural area, cropland area, and pasture area) in logarithms on the onset of the Priority List in 2008. Since treatment is staggered, we restrict attention to the municipalities that join the Priority List in 2008 and those that never join as a pure control group. We only include municipalities in the Brazilian Legal Amazon, as they are more likely to resemble Priority List municipalities. Standard errors, in parenthesis, are calculated via bootstrap with 50 repetitions. * p<0.10, ** p<0.05, *** p<0.01

Table 2: Effects of Priority List on Crop-specific Agricultural Outcomes

	(log) Revenue	(log) Area	(log) Price	(log) Yields	N observations
Ag Value Added	0.190***				
	(0.036)				13,685
Coffee	0.252	0.274	0.088**	-0.034	
	(0.255)	(0.291)	(0.037)	(0.129)	1,780
Cassava	-0.137	-0.116	0.022	-0.027	
	(0.098)	(0.097)	(0.036)	(0.026)	14,140
Beans	-0.495***	-0.383**	0.076**	-0.130***	
	(0.178)	(0.157)	(0.034)	(0.050)	8,660
Maize	0.515***	0.390**	-0.056***	0.150***	
	(0.181)	(0.166)	(0.020)	(0.045)	13,280
Sugar	-0.307	-0.392	0.133	-0.053	
	(0.381)	(0.358)	(0.118)	(0.058)	3,460
Soy	0.363**	0.396**	-0.003	0.004	
	(0.175)	(0.165)	(0.020)	(0.034)	1,920
Orange	-0.084	-0.110	0.110	-0.068	
	(0.283)	(0.177)	(0.074)	(0.065)	3,780
Banana	0.312*	0.154	0.185***	-0.033	
	(0.161)	(0.142)	(0.049)	(0.044)	10,200
Cocoa	0.450	0.567***	-0.045	-0.082	
	(0.310)	(0.192)	(0.035)	(0.067)	1,760
Cotton	-0.390	-0.282	-0.024	0.026	
	(0.266)	(0.255)	(0.044)	(0.060)	480
Rice	-0.100	-0.193	0.026	0.092**	
	(0.173)	(0.139)	(0.029)	(0.038)	10,300

Note: This table shows the results of the municipality-year-level the synthetic differences in differences regressions of agricultural value added and crop-specific outcomes (specifically: revenue from crop, area harvested, average farm-gate price, and average yields) in logarithms on the onset of the Priority List. The first row is a regression as (1) but with outcome the log of agricultural value added as obtained from the system of regional accounts. The second row onwards are regressions as (1) with outcomes calculated from the yearly municipal agricultural survey PAM. Standard errors are calculated via bootstrap with 50 repetitions. We only include municipalities in the Brazilian Legal Amazon, as they are more likely to resemble Priority List municipalities. Years in which the crop is not grown (according to the data) are dropped. Subsequently, municipalities that have not grown a crop (in a year that was not dropped in the previous step). Standard errors in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

3.3 Effects of Protected Areas

3.3.1 Econometric specification

Unlike the Priority List policy, the establishment of protected areas (both Conservation Units and Indigenous Territories) does not necessarily coincide with municipal borders. Hence, we split the Brazilian territory in hexagons with 10 km width, and classify each of them as being or not part of a protected area if at least 50% of its surface falls within the demarcated boundaries.

I use the hexagon-level data to estimate a Regression Discontinuity Design around the border of the conservation unit. The baseline specification is:

$$\text{(log) ForestArea}_{ht} = \delta_t + \gamma_{m(h)} + f(\text{Distance}_{ht}) + \beta D_{ht} + \epsilon_{ht} \tag{3}$$

Where (log) ForestArea$_{ht}$ is the logarithm of the total forest area observed in hexagon h, at year t, δ_t are year fixed effects, $\gamma_{m(h)}$ are municipality fixed effects, $f()$ is a continuous function, Distance$_{rt}$ is the running variable measuring the distance in km to the border of the nearest conservation unit where negative (positive) values mean that the hexagon falls inside (outside) the protected area, and D_{ht} is a dummy variable indicating whether hexagon h falls within a protected area at time t. $D_{ht} = 1\{\text{Distance}_{ht} \leq 0\}$. The coefficient of interest in β, identifying the effect on deforestation of being inside the conservation area. We use forest area instead of deforestation as an outcome because protected areas are typically established in regions with very low levels of deforestation, so the numeric interpretation of the effect on forested area is clearer.

Validity. The validity of the RD design relies on the assumption of continuity of the outcome variable with respect to the running variable in the absence of treatment. In other words, in the absence of the protected areas, deforestation does not see a discontinuous spatial jump at $D_{ht} = 0$. A potential concern that arises with this specification is that, given the size of Brazil, the data was coarsened to the 10 km hexagon level and hence the distance to the border (running variable) is discrete. Therefore we cannot consider an arbitrarily small neighbourhood of the cut-off. To test the continuity assumption in this setting, we estimate the same Regression Discontinuity design considering only hexagons located in future protected areas. For the results of these exercises, see section 3.3.3.

Table 3: Regression discontinuity estimates for the effect of Protected Areas on forested area

	(Outcome: log-forested area)		
	(1)	(2)	(3)
Estimated Gap (PA: CU or IT)	0.1430***	0.2396***	0.2378***
	[0.0425]	[0.0343]	[0.0356]
Quad spline	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Mun FE	No	Yes	Yes
Year X mun. FE	No	No	Yes
R2	0.0691	0.6081	0.6259
Observations	2.16e+06	2.16e+06	2.16e+06

Note: This figure shows the results of the hexagon-year-level regression discontinuity of (log) forest area on the boundaries of Protected Areas (PA). PAs include both Conservation Units (CU) and Indigenous Territories (IT). The regression result presented displays coefficient β in (3) under three different specifications. The regression includes years 1985-2022 and all hexagons within 50km of a PA boundary. In all of them $f(\cdot)$ is a quadratic spline, split around the threshold (0), of the distance to the PA's boundary, which is negative inside and positive outside. Column (1) controls for year fixed effects only to control for common trends. Column (2) includes year and municipality fixed effects to control for fixed characteristics at the municipality level. Column (3) includes municipality-year fixed effects to control for municipality-specific time trends. Standard errors in parenthesis. *p<0.1, **p<0.05, *** p<0.01.

3.3.2 Results

Table 3 show the estimated β from Equation 3 where f is a quadratic spline, adding different sets of fixed effects: (1) has only year fixed effects, (2) has only municipality fixed effects, and (3) has municipality-year fixed effects. The results suggest that there is an increase of between 15% and 27% in the forest coverage of hexagons inside of a protected area as compared to those just outside. The preferred specification is (3), as it controls for the fact that the process of establishing a protected area is a political one and changes in the municipal government or administrative bureaucracy may correlate with changes in protected area status.

Figure 6 illustrates the regression discontinuity results graphically by showing average (log) forest area in bins of multiples of 10 km of distance from the border of a protected area. Panel (a) on the left shows the simple regression discontinuity specification with a quadratic fit and no fixed effects, whereas panel (b) on the right has as dependent variable the (log) forest area residualised by municipality-year fixed effects. Both specification show a clear jump in forested area of around 0.2 log-points (or a 22% increase) at the demarcated border. In panel (a) we can see that hexagons deeper inside a protected area typically have higher forest cover than those closer to the border, however, this relationship seems to change discontinuously around the border.

3.3.3 Robustness

In order to test the validity of the regression discontinuity design, we investigate the plausibility of the smoothness assumption by comparing what happens at the border a future protected area before it is established. To do so we run the following placebo test.

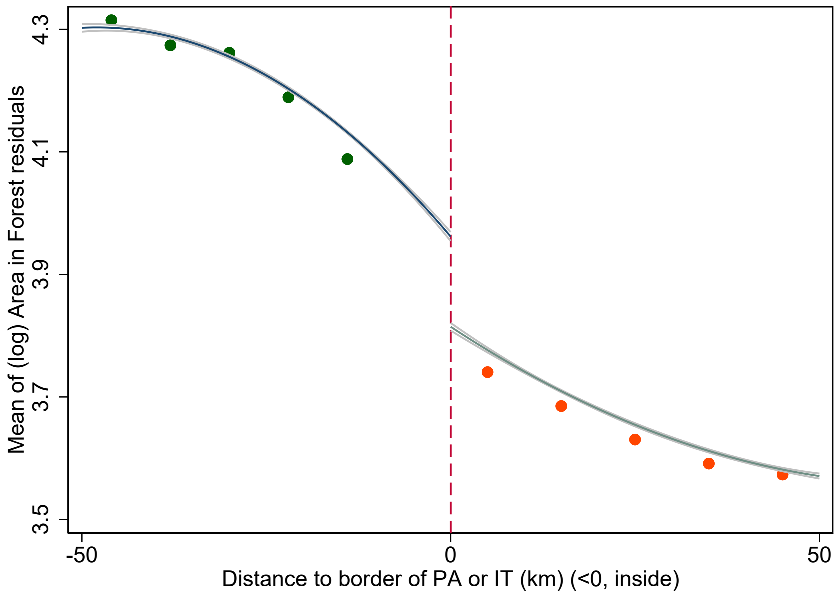
$$\text{ForestArea}_{ht} = \delta_t + \gamma_{m(h)} + f(\text{MinDistance}_h) + \tilde{\beta}\tilde{D}_h + \epsilon_{ht}, \tag{4}$$

where $\text{MinDistance}_h \equiv \min_t \text{Distance}_{ht}$ is the time-invariant minimum distance that a hexagon h ever has from a Protected Area, which is also the last one because they never get dismantled and hence Distance_{ht} can only decrease, and $\tilde{D}_h = 1\{\text{MinDistance}_h \leq 0\}$. The sample is restricted to observations of hexagons h at times t for which that minimum distance to a protected area, MinDistance_h, is achieved in a certain number of years. That is, for each hexagon, we can define an event time $T(h)$ from which the distance does not further decrease and for the placebo test we consider only observations (h, t) such that $t < T(h)+k$ where k is the number of years before establishment that we want to consider. Table 4 below shows the corresponding estimates for the RD parameter $\tilde{\beta}$ for $k = 10$ for columns (1) and (2) and for $k = 5$ for columns (3) and (4). Columns (1) and (3) have only year fixed effects whereas (3) and (4) have municipality-year fixed effects. While no effects are found more than 10 years before, there is a discontinuity 5 years before. A discontinuity around the border of a future protected area before its implementation can be due to a number of factors, for example: (i) lengthy legal disputes over the demarcation of new protected areas, during which deforestation decreased before the final settlement and establishment [14] or (ii) historical occupation of the area by indigenous people whose livelihood depends on the preservation of the forest before legal demarcation of the Protected Area.

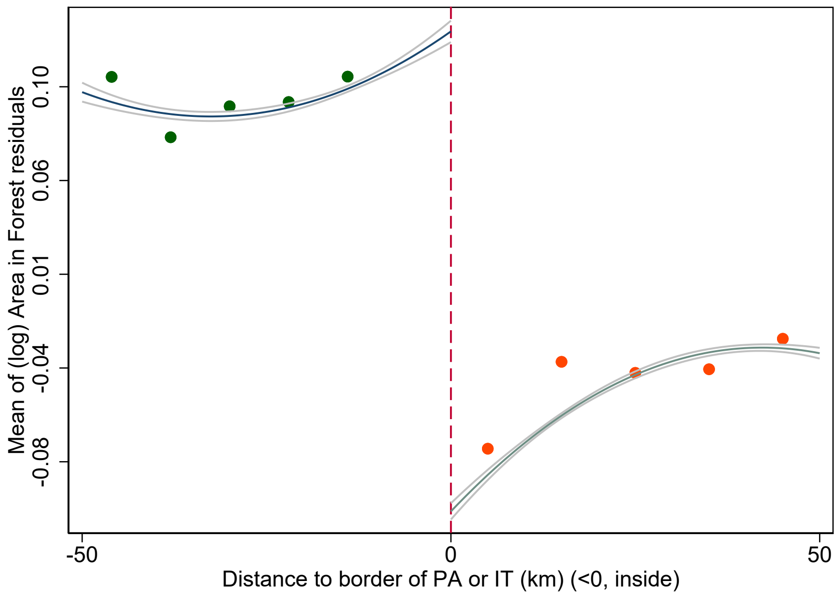
Figure 7 illustrates this graphically. The four plots show the same RD graph as in figure 6, panel (a), but for different event times relative to the establishment of the nearest protected area. Clockwise from the top-left: (i) more than 10 years before establishment, (ii) up to 10 years before, (iii) up to 10 years after, and (iv) more than 10 years after. Appendix figure 26 show the exact same comparison, but now including year and municipality fixed effects. Adding municipality-year fixed effects there is a statistically significant discontinuity for all event time groups but the gap seems very small more than 10 years before and it seems to be clearly widening over time.

[14]This is particularly likely in the case of Indigenous Territories. Their establishment follows a judicial process that includes several stages: study, delimitation, declaration, homologation, and regularisation, that

Figure 6: Discontinuity in forested area around borders of protected areas.



(a) No controls



(b) Municipality-Year FEs

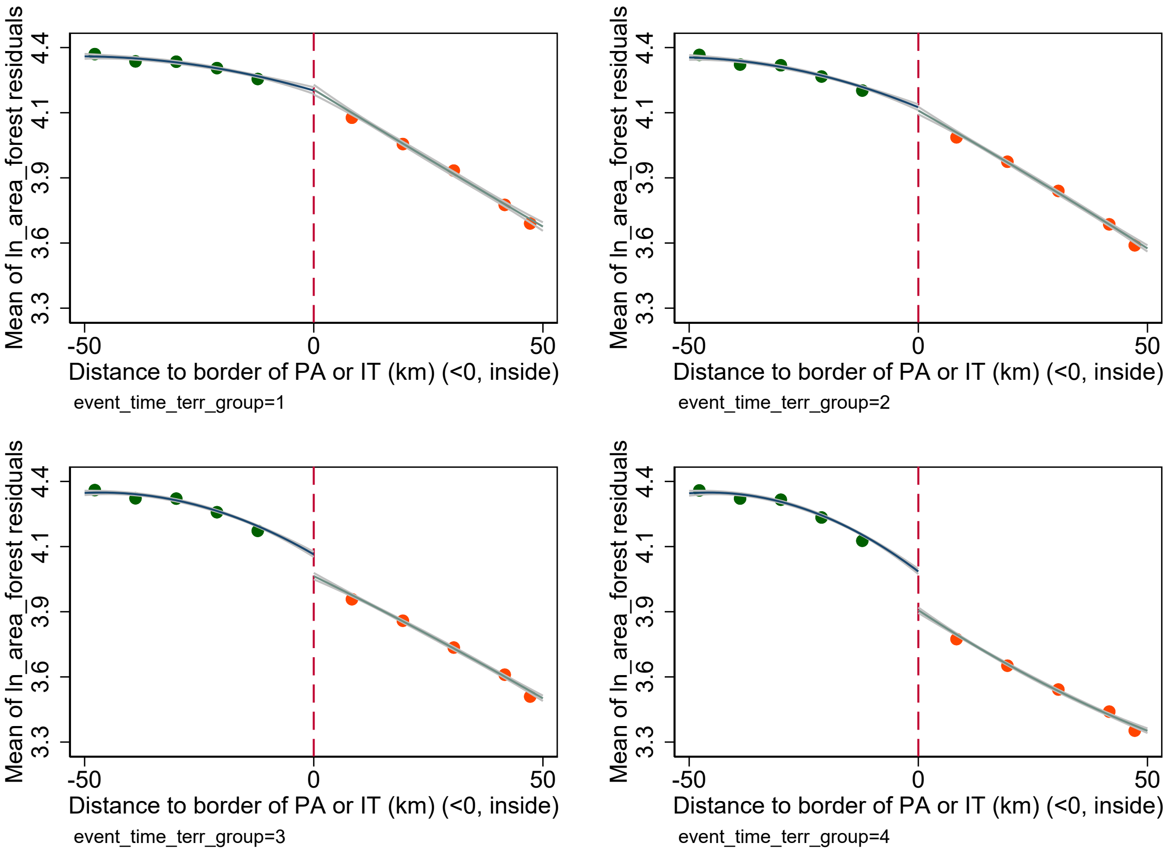
Note: This figure illustrates the discontinuity in forested area around the borders of protected areas. Each dot represents the mean total log-forested area within bins of 10 km around the border of all protected areas, from 50km inside of 50km outside. The x-axis shows distance to the border, with negative (positive) values indicating the area inside (outside) the protected area. On top of the dots are the quadratic fits of both distance trends. The top panel illustrates the raw averages. The bottom panel illustrates averages of the residuals of a regression of log-forested area on municipality-year fixed effects, which controls for differential trends at the municipality level. Since there are observations for multiples years (1985-2022) the snapshots with varying different protected area-borders are pooled together so that a hexagon that in 1985 is 50km away from the border could be 10 km inside a border in 2020. For each hexagon this distance can only decrease over time.

Table 4: Placebo Regression Discontinuity

	10+ years before		5+ years before	
	(1)	(2)	(3)	(4)
Estimated Placebo Gap	0.0387	0.0678	0.2509***	0.0777**
	[0.0620]	[0.0450]	[0.0583]	[0.0336]
Quad. spline	Quad. spline	Quad. spline	Quad. spline	Quad. spline
Year FE	Yes	Yes	Yes	Yes
Year X mun. FE	No	Yes	No	Yes
Years before	10+	10+	5+	5+
R2	0.0801	0.6756	0.0513	0.6742
Observations	3.22e+05	3.22e+05	2.82e+05	2.82e+05

Note: This figure shows the results of the hexagon-year-level regression discontinuity of (log) forest area on the boundaries of Protected Areas (PA). PAs include both Conservation Units (CU) and Indigenous Territories (IT). The regression result presented displays coefficient β in (4) under four different specifications. The regression includes years 1985-2022 and all hexagons within 50km of a PA boundary in 2022. In all of them $f(\cdot)$ is a quadratic spline split around the threshold (0) of the distance to the PA's boundary, which is negative inside and positive outside. Columns (1) and (2) include hexagons only 10+ years before they reach their minimum distance to a PA, that is, 10+ years before the closest PA to them (or in which they are contained) is established. Columns (3) and (4) include hexagons 5+ years before that occurs. Columns (1) and (3) control only for year fixed effects. Columns (2) and (4) control for municipality-year fixed effects. Standard errors in parenthesis. *p<0.1, **p<0.05, *** p<0.01.

Figure 7: Discontinuities in forested area around borders of Protected Areas, by: period relative to the introduction of conservation policy



Note: This figure illustrates the discontinuity in forested area around the borders of protected areas, before and after they are protected. More specifically: the top-left panel considers 10+ years before the protection of the nearest area, the top-right 0-10 years before, the bottom-left 0-10 years after, and the bottom-right 10+ years after. Each dot represents the mean log-forested area within bins of 10 km around the border of all protected areas, from 50km inside of 50km outside. The x-axis shows distance to the border, with negative (positive) values indicating the area inside (outside) the protected area. Here the hexagons are classified according to the minimum (and final, since it can only decrease) distance they ever have from a Protected Area across all periods in the sample, but their forest area is only considered for years in which (i) they area 10+ years from reaching that minimum distance, (ii) they are 0-10 years away from reaching that minimum distance, (iii) they reached it 0-10 years ago, (iv) they reached it 10+ years ago.

3.4 General Equilibrium Effects and SUTVA

As previously discussed, an assumption required for the validity of both reduced-form methods discussed above is Stable Unit of Treatment Variable Assumption (SUTVA). Consider the treatment D_i a binary variable equal to 1 if a place is subject to a conservation policy, 0 otherwise. Assume that the potential outcome of i depends on two factors, its own conservation status, and the price of land, which depends on the conservation statuses in all regions $Y_i(D_i, P(\vec{D}))$. Even if treatment was as good as randomly assigned, but SUTVA did not hold, we would be estimating a combination of the desired treatment effect and leakage as shown below

$$\begin{aligned}
\widehat{\beta} \rightarrow & \mathbb{E}\big[Y_i(1, P(\vec{D}_{policy}) - Y_i(0, P(\vec{D}_{policy})\big] \\
= & \underbrace{\mathbb{E}\big[Y_i(1, P(\vec{D}_{nopolicy}) - Y_i(0, P(\vec{D}_{nopolicy})\big]}_{\text{Pure effect of policy on treated}} \\
+ & \underbrace{\mathbb{E}\big[Y_i(1, P(\vec{D}_{policy}) - Y_i(1, P(\vec{D}_{nopolicy})\big]}_{\text{Leakage on treated}} \\
- & \underbrace{\mathbb{E}\big[Y_i(0, P(\vec{D}_{policy}) - Y_i(0, P(\vec{D}_{nopolicy})\big]}_{\text{Leakage on untreated}}.
\end{aligned}$$

A reduced-form estimate, therefore, would include both the desired ATET and potential leakage onto untreated areas. Therefore, it requires an assumption about the nature of the second right-hand side term in the equation above. Typically, the implicit assumption is that there is no leakage, i.e. $Y_i(d, P_1) = Y_i(d, P_2)$, which results in an overestimation of the true treatment effect.

Even when leakage is explicitly considered, reduced-form estimates requires assuming which regions are prone to leakage, and which regions can be considered as uncontaminated controls. A common approach is to assume that neighbouring areas are prone to leakage, whereas places further away from treatment are not affected in any way. Whereas this might be plausible from a purely spatial perspective, it has two problems: (i) it requires an arbitrary distance cut-off that separates areas that are susceptible to leakage from areas that are not, and (ii) it ignores other that the best regions to substitute the lost agricultural production may not be necessarily be neighbours.

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can take decades

4 Deforestation in Spatial Equilibrium

We build a spatial multi-sector general equilibrium model that explicitly captures the key features of the spatial distribution of agriculture, the economic forces at play in the market for land, and frictions to movement of goods and labour via internal trade and migration.

Stylised facts Our theoretical framework is motivated by observed spatial patterns in deforestation and agriculture across Brazil, as illustrated by Figures 8 and 9. From Figure 8, we can see that areas with more deforestation have lower GDP per capita[15], and lower market access[16]. From Figure 9, we can see that areas with higher deforestation have lower agriculture productivity[17] and higher share of agricultural area dedicated to pasture, which is typically much more land intensive than crop growing.

Overall, deforestation seems to happen in poorer and more remote areas, where land is dedicated to activities that are more land-intensive and less productive. There are differences in how costly it is to deforest land, as well as stark differences in agricultural productivities[18]. Given the large difference in local economic development, Brazil's continental dimensions and large heterogeneities in transportation infra-structure, goods and workers face non-negligible mobility costs. Moreover, the demand for agricultural land is not perfectly inelastic as farmers can adjust land intensity and consumers can choose between different goods depending on their relative prices.

Mechanisms for leakage In our framework, a local anti-deforestation policy is interpreted as an exogenous shock to the local supply of agicultural land. To quantify spatial leakage, we consider two key mechanism through which a negative supply shock generates increased deforestation elsewhere. The first mechanism operates through the market for agricultural goods. A negative shock to the local supply of agricultural land decreases the supply of agricultural goods. The extent to which this avoided deforestation leaks elsewhere depends on the extent to which goods are substitutable across space and can be produced by clearing forest elsewhere. The second mechanism operates through the market for labour. A local reduction in deforestation coming from a shock decreases the demand for agricultural labour, changing workers' migration incentives. Inflows of workers to regions without

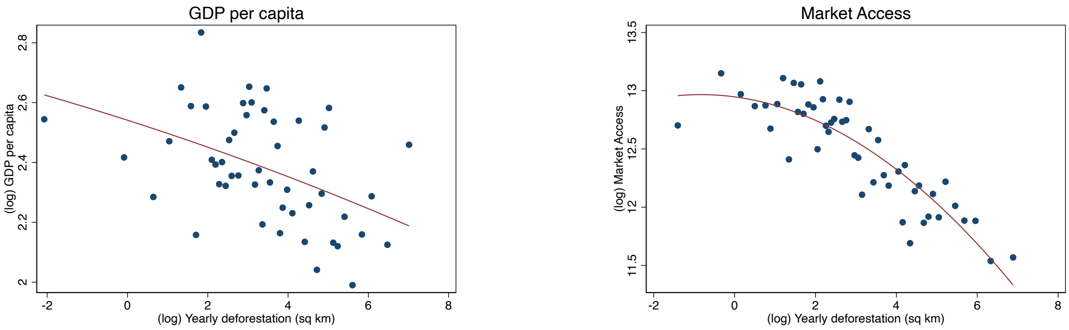
[15]Deforestation in Brazil is strikingly concentrated in space. Out of the 558 micro-regions that make up Brazil, the top 20 account for almost 40% of the total yearly deforestation. Regions with high levels of deforestation are very different ecologically and economically to the rest of Brazil.

[16]Defined by the first order approximation in (Donaldson and Hornbeck, 2016) $MA_d = \sum_o (\tau_d^o)^{\sigma-1} L_o$ where τ_d^o is the ice-berg trade cost between o and d as estimated in section D.4

[17]Defined as agriculture revenue per hectare

[18]This is true for the agricultural sector as a whole, as well as for spatial differences in cultivation of specific crops. It is also true both when measuring productivity as revenue per hectare and revenue per worker.

Figure 8: Correlates of average yearly deforestation rate

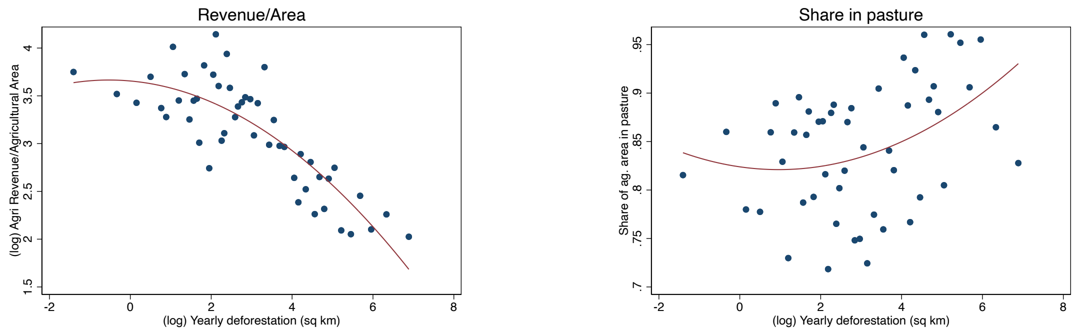


(a) log GDP per capita

(b) Market access

Note: This figure illustrates the correlation between average yearly deforestation rate and economic characteristics: log-GDP per capita (left panel) and market access (rigth panel - defined as). The dots represent the mean of the y-axis variable for 50 bins of log-yearly deforestation.

Figure 9: Correlates of average yearly deforestation rate



(a) Agricultural productivity

(b) Land intensity

Note: This figure illustrates the correlation between average yearly deforestation rate and economic characteristics: agricultural productivity (left panel - defined as the ration between agricultural revenue and agricultural area), and share of agricultural land dedicated to pasture (rigth panel). The dots represent the mean of the y-axis variable for 50 bins of log-yearly deforestation.

anti-deforestation policies will increase the demand for agricultural land, raising incentives to deforest[19].

To capture these channels, our model considers deforestation as an intermediate economic sector that supplies land as a factor of production for agriculture. Regions differ in the

[19] A useful benchmark is a flat economy where all land is made equal, workers and goods can move freely, and demand for agricultural land is perfectly inelastic. In this case, leakage would be 100%: banning deforestation entirely in one region would have no global effect, as it would be perfectly leakeg to other regions - the demand for agricultural goods would be the sole determinant of the amount of agricultural land, and hence of the level of deforestation. Our model departs from all of those assumptions in ways that are consistent with the data.

sectoral productivities for agricultural and non-agricultural production, as well as in their productivity in producing land via deforestation[20].

Model features We conceptualise deforestation as an investment in agricultural land that accumulates over time. Brazil is modelled as a closed economy with domestic trade and migration. The model considers Brazil's 558 microrregions[21] indexed by r, which differ on their sectoral productivities, land endowments, and amenities. The economy is composed of $K+1$ sectors: K agricultural commodities that use land and labour as inputs and have different labour shares, and one non-agricultural sector that uses only labour. Additionally, we consider deforestation as a sector that uses a composite investment good in order to produce agricultural land for the K agricultural sectors. There is trade between municipalities subject to iceberg costs. Consumer preferences are non-homothetic, represented by the Price-Independent Generalized Linear preference formulation (Boppart, 2014). Final goods in each sector are a composite of regional varieties aggregated with constant elasticity of substitution σ and a final agricultural good is a composite of the various agricultural commodities aggregated with constant elasticity of substitution θ.

The model features a sequence of static spatial equilibria linked by the laws of motion of land and labour. The law of motion of land is determined by deforestation and the law of motion of labour is determined by migration and population growth.

4.1 Land use dynamics: the endogenous accumulation of land

Initially, each region r is endowed with L_{r0} workers, T^A_{r0} units of agricultural land area, and T^N_{r0} units of terrestrial natural ecosystems which can be converted into agricultural land.

For most of this section, we omit the time subscript and treat the equilibrium as static. However, since agricultural land accumulates, it is a time-varying quantity. Assuming a fixed forest regrowth rate ρ, at letting T^D_{rt} be the level of deforestation, agricultural land evolves according to

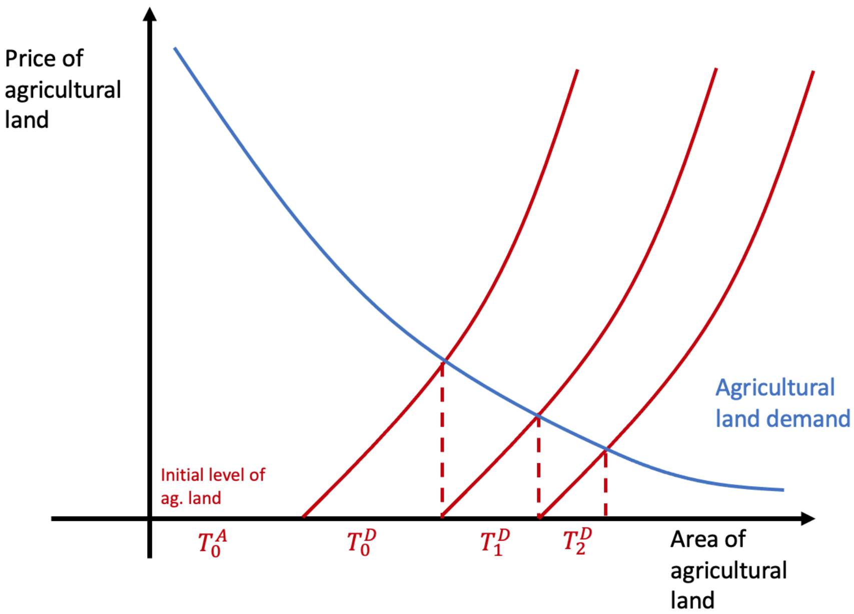
$$T^A_{rt+1} = T^A_{rt}(1-\rho) + T^D_{rt}.$$

The following simple agricultural land market graph helps visualise how land evolves over time. In this simple graph, land demand is fixed, there is only one region, there is no forest regrowth, and the deforestation supply curve does not change over time. In particular,

[20]Deforestation productivity can be thought of as region-specific factors that govern how suitable a particular region is for forest cutting. It can include natural factors (forest density, type of vegetation, altitute, weather patterns, geographical features), infra-structure and accessibility, the political environment and the level of enforcement of anti-deforestation laws.)

[21]This is typically considered the aggregation level that is most closely associated with a local market, see for example Dix-Carneiro and Kovak (2017)

Figure 10: The market for agricultural land over time



Note: This figure illustrates how agricultural land would accumulate over time. In this graph, land demand is fixed, there is only one region, there is no forest regrowth, and the deforestation supply curve does not change over time.

the scarcity of forest does not change its value relative to agricultural land. The graph illustrates in what sense the supply for deforestation is conceptualised as yearly. This means that the decreasing returns to scale of the deforestation production function, discussed below, reflect how deforesting more land within a single year is increasing costly, which could reflect resource constraints of the deforesting agents. A decade-long deforestation supply curve would be flatter. With the assumptions in the graph (fixed demand for land, fixed yearly deforestation supply, no forest growth) eventually the whole forest would be converted to agriculture. However, in practice, we will relax all of these assumptions: the demand for and will change in response to population growth, migration, and productivity shocks, and past land accumulation; there will be a rate of forest regrowth; and the costs of deforestation will go up as there is less forest area left in a region.

4.2 Population dynamics: Migration

As in Eckert and Peters (2022), individuals born in a location of origin o can choose to live in destination d according to the migration costs μ_{od}, the utility at the destination $V(e_d, p_d)$, the amenities at destination d, B_d, and an idiosyncratic shock $\nu_d(i)$, drawn from a Frechet distribution with parameter ϵ. The origin-destination specific migration utility $\mathcal{U}_{od}$ is given by:

$$\mathcal{U}_{od}(i) = V(e_d, p_d)B_d\mu_{od}\nu_d(i).$$

Therefore, from the Frechet nature of the shock, the share of people who move from o to d is given by the following expression[22]

$$\rho_{od} = \frac{(V(e_d, p_d)\mu_{od}B_d)^\epsilon}{\sum_{r=1}^{R}(V(e_r, p_r)\mu_{or}B_r)^\epsilon}.$$

Hence the law of motion of population will be given by the following equations

$$N_{dt} = \sum_{o=1}^{R} \rho_{rd}N_{ot}, \quad N_{ot} = g^N_{ot-1}N_{ot-1}$$

where g^N_{ot-1} is the growth rate of population in origin region o at time t.

4.3 The market for deforestation

Deforestation is modelled as a costly investment in the production of agricultural land, which is a factor of production for the agricultural sector. We can think of deforesters as atomistic agents operating in a perfectly competitive market where they access forested land, pay the fixed cost of clearing it, and sell it at the price of agricultural land. We model the aggregate deforestation production function so that it has decreasing returns to scale. This motivated by the fact that, within each time period, the forest that is closer to the edge is cheaper to access and clear. This means that each additional dollar spent deforesting is less productive. The aggregate deforestation production function is such that if an amount I^D_r of the final good, bought at price p_r, is invested in deforestation, it delivers T^D_r units of agricultural land according to

$$T^D_r = Z^D_r(I^D_r)^\delta, \tag{5}$$

where Z^D_r is the region-specific "deforestation productivity", and $\delta \in (0, 1)$ governs the returns to scale of the production function. The returns of each square kilometre of deforested land equal the value of agricultural land in a given region, q_r. We can interpret Z^D_r and δ as the productivity parameters that dictate the aggregate (convex) costs of deforesting, $C^D_r(T^D_r, p_r; Z^D_r, \delta) = p_r(Z^D_r)^{-\frac{1}{\delta}}(T^D_r)^{\frac{1}{\delta}}$.

Our model of the market for deforestation has two defining features. First, land in natural ecosystems is open access, which means that the future value of the forest is fully

[22] This includes ρ_{oo}, i.e. the share of people from region o who choose to stay in region o.

discounted[23]. Second, there is free entry of deforesters. Accordingly, they enter the deforestation market as long as there are non-negative marginal profits, so that the equilibrium level of deforestation is when marginal costs, $MC_r^D = \partial C_r^D(T_r^D, p_r; Z_r^D, \delta)/\partial T_r^D$, equal marginal revenues, $MR_r^D = q_r$,

$$T_r^{D*} = \underbrace{(Z_r^D)^{\frac{1}{1-\delta}}}_{\text{Local Factors}} \underbrace{\left(\frac{\delta q_r}{p_r}\right)^{\frac{\delta}{1-\delta}}}_{\text{Equilibrium Effects}} . \tag{6}$$

Supply side of deforestation

The curve $T_r^{D*}(q_r/p_r)$ is the region-specific deforestation supply curve: how deforestation responds to the local relative price of land. It depends on two parameters δ, the returns to scale of deforestation in one year, and Z_r^D, the location-specific deforestation productivity.

The returns to scale of deforestation δ is taken to be the same for all of Brazil, and it governs the supply elasticity of deforestation to real land prices, which equals $\frac{\delta}{1-\delta}$. That is, for a 1% increase in the value of agricultural land relative to that region's price index, deforestation goes up by $\frac{\delta}{1-\delta}$%. See section 5.1.1 in the appendix for the estimation of δ.

Z_r^D is the source of regional heterogeneity in deforestation costs. It reflects differences in characteristics such as, (i) local environmental conditions that influence how difficult it is to deforest, such as rainfall and temperature, (ii) the level of enforcement of anti-deforestation policies, (iii) revenues obtained from the act of deforestation itself, for example through the sale of wood, and (iv) the option value of keeping land as forest. While most of these things are difficult to observe and quantify, we correlate them to the structurally estimated Z_r^D's and find that the current area of unprotected forest in a region, T_r^F is a strong predictor of Z_r^D. A log-log model does a remarkably good job at describing their empirical relationship in cross-sectional data. Therefore, let

$$Z_r^D = \overline{Z_r^D}(T_r^F)^{\psi}.$$

It is estimated so that it perfectly explains observed differences in levels of deforestation in regions that cannot be explained by agricultural rents and market access, which are reflected by q_r and p_r respectively. In turn, prices come from the inversion of a spatial equilibrium model in each time period, as described in 5.2. Intuitively, we estimate the demand

[23] Around 50% of deforestation in the Amazon over the past few years has happened in untitled public lands. From the remaining 50%, about half has happened in rural settlements where land was and half in private properties. Although the amount of deforestation in private properties is not negligible, about 25% of the total, rights over forested land are insecure even within private property. This is due to it historically being often regarded as "unproductive" and thus subject to the ownership claims of squatters. See (Alston et al., 1999) for an in depth description of property rights in the Brazilian Amazon frontier.

for agricultural land from farmers, which in turn depends on the demand for agricultural products from consumers, and then, using the observed data on deforestation, we calculate the productivity of deforestation as a residual that rationalises their spatial distribution. To be more concrete, for a given level of observed deforestation, a region with lower market access and lower agricultural productivity will have a higher estimated Z_r^D.

4.4 Technology: local demand for workers and land

In order to estimate the demand for land in each region, we first need to impose some structure on the firms operating in each region. This will determine how they demand different factors of production, land and workers, given productivities and prices. Productivities will be treated as exogenous fundamentals to be backed out from the model and prices will depend on the full (static) equilibrium which takes into account consumer preferences and trade costs.

There are four broad sectors: three agricultural sectors with varying land intensities, and non-agriculture which uses no land for production. Regions produce a differentiated variety of each of these four goods as in Armington (1969) that consumers combine with Constant Elasticity of Substitution as in Anderson (1979). The market in each of the four sectors is composed of perfectly competitive firms with constant returns to scale. The local non-agricultural goods are a product of only labour with regional productivity Z_r^{NA}, so that $Y_r^{NA} = Z_r^{NA} L_r^{NA}$. The agricultural goods, indexed by k, are a Cobb-Douglas function of land and labour with constant returns to scale and regional productivities Z_r^{Ak}, and a share of land equal to α_k, so that

$$Y_r^{Ak} = Z_r^{Ak} (L_r^{Ak})^{1-\alpha_k} (T_r^{Ak})^{\alpha_k}.$$

Goods of sector s are produced to be sold at origin prices p^{so}.

In a competitive equilibrium, the rental rate of agricultural land v_r equals the marginal product of agricultural land and the wages in each sector equal the marginal product of labour in each sector. Assuming simple adaptive expectations (i.e. agents assume the future rental rate of land equals today's) and a discount rate of β, land should be priced at its expected present value,

$$q_r = \frac{1}{1-\beta(1-\rho)} v_r.$$

Our data allows us to get agricultural revenues (see section 5.2) and use them to get v_r as

$$v_r = \sum_k \alpha_k \frac{p^{Akr} Y_r^{Ak}}{T_r^{Ak}}.$$

4.4.1 Wage gaps and occupational choice

In order to allow for a gap between agricultural and non-agricultural wages, as we consistently find in the data, we rely on a model like the one introduced by Lagakos and Waugh (2013) and applied to the context of Brazil in Alvarez (2020). In this model, individuals draw idiosyncratic productivities for agriculture and non agriculture from a joint distribution $F(z_i^A, z_i^{NA})$ and given their observed productivities for each sector[24]. Workers choose sector in order to maximise their wage income, so that they work in non-agriculture if and only if $z_{ri}^{NA} w_r^{NA} \geq z_{ir}^{A} w_r^{A}$. Firms set wages per efficiency unit (w_r^A, w_r^{NA}) that equal the marginal product of a worker with unit productivity in that sector. By L_r^s we refer to the total labour efficiency units in sector $s \in \{A, NA\}$ in region r, which is equal to the number of workers multiplied by the expected productivity of those who choose to work in sector s. Since the idiosyncratic productivities in each sector are not independent draws, there will be income gaps, the average wage income $(\overline{y}_r^{LA}, \overline{y}_r^{LNA})$ will not be equalised across sectors.

4.5 Preferences: demand for goods

Having characterised the factors that determine the demand for agricultural land given the prices of agricultural goods, let us now turn to the preferences that governs the demand side of agricultural goods markets.

Non-homothetic preferences between agricultural and non-agricultural goods

Consumers have PIGL preferences as in Boppart (2014) over agricultural and non agricultural goods. These preferences are represented by the following indirect utility function:

$$V(e, \vec{p}) = \frac{1}{\eta}\left(\frac{e}{(p^A)^{\phi}(p^{NA})^{1-\phi}}\right)^{\eta} - \nu\left(\frac{p^A}{p^{NA}}\right). \tag{7}$$

Where p^A and p^{NA} are prices of agricultural and non-agricultural sector, e is total expenditure, and η, ϕ, and ν are exogenous parameters. By Roy's identity, after relabelling the price of the composite consumption good $p \equiv (p^A)^{\phi}(p^{NA})^{1-\phi}$, the expenditure share in agricultural goods equals

$$\vartheta^A(e, \vec{p}) = \phi + \nu \underbrace{\left(\frac{p^A}{p^{NA}}\right)}_{\text{relative price effect}} \underbrace{\left(\frac{e}{p}\right)^{-\eta}}_{\text{Income effect}}.$$

[24]The joint distribution is taken to be, as in Alvarez (2020), a Frank copula or two Frechet distributions with shape parameter χ^A and χ^{NA} and correlation ι

CES aggregation between goods

The agricultural good is, in turn, a CES aggregate of agricultural goods $k \in \{$beef, temporary crops, perma with elasticity of substitution θ, so that the agricultural price index p^A is equal to $p^A \equiv \left(\sum_{k=1}^{K}(p^{Ak})^{1-\theta}\right)^{\frac{1}{1-\theta}}$ and the share of agricultural good k in the overall agricultural expenditure is given by $\left(\frac{p^{Ak}}{p^A}\right)^{1-\theta}$.

CES aggregation between origins

Each of the $3+1$ final goods (the three agricultural goods and the non-agricultural good) is, in turn, a CES composite of differentiated regional varieties produced in region r, with a constant elasticity of substitution σ. Trade is taken to have symmetric iceberg trade costs $\tau_d^o \geq 1$ that do not vary by good so that a consumer from region d pays the origin price of a good from region o scaled by the bilateral iceberg trade cost. Thus, the share of goods g (which can be beef, temporary crops, perennials, or non-agricultural goods) consumed in region d, that is produced in region o, is given by[25]

$$\pi_d^{go} = \frac{(\tau_d^o)^{1-\sigma}(p^{gr})^{1-\sigma}}{\sum_{r=1}^{R}(\tau_d^r)^{1-\sigma}(p^{gr})^{1-\sigma}}. \tag{8}$$

I take σ from Eckert and Peters (2022) to be 9.[26] Having a value for σ, we use inter-state trade flow data from 1999 and 2017 to estimate a gravity equation derived from 8 along with the assumption that the iceberg trade costs depend on distance according to $\tau_d^o = (\text{distance}+1)^{\kappa}$.

4.6 Market clearing: closing the model

In order to close the model, we equalise the revenues from producers of good g from origin o to the sum of the expenditures of consumers in that good from across all regions d of Brazil. These expenditures equal the trade share of d to o times the total consumption of region d in good g,

$$p^{go}Y_o^g = \sum_{d=1}^{R} \pi_d^{go} X_d^g. \tag{9}$$

[25] To differentiate between origin and destination prices we shall indicate the region of origin with a superscript and the region of destination with a subscript. Then the farm-gate price of temporary crops from o is $p^{A,temp,o}$, the price of temporary crops from o faced by consumers in d is $p_d^{A,temp,o} = p^{A,temp,o}\tau_d^o$, and the consumer price index of temporary crops in destination d equals $p_d^{A,temp} = \sum_{o=1}^{R}(\tau_d^o)^{1-\sigma}(p^{A,temp,o})^{1-\sigma}$.

[26] Given that this context is closer to Domiguez-Iino (2021), we will also invert the model and simulate counterfactuals with values up to $\sigma = 15$, given his estimated elasticity of substitution between "counties" in Brazil and Argentina of around 13.

Aggregate consumption in a region

The overall expenditure of a region in each good can be calculated in three steps. First, we estimate the aggregate share of consumer expenditure in agriculture ϑ_r^A, which will depend on the PIGL preference parameters, the relative price of agricultural goods, the aggregate expenditure, and the distribution of incomes as dictated by wages and the joint distribution of productivity shocks. Given the non-homothetic nature of preferences for agricultural goods and the fact that there is within-region inequality due to the productivity shocks introduced to generate a wage gap, the formula for ϑ_r^A is not very pretty. Intuitively, in the face of higher inequality, the share of expenditure in agriculture will be lower because a higher share of earnings will accrue to those who spend proportionally less in agriculture. Then, given the fact that the investment good is a Cobb-Douglas aggregate of the agricultural and non-agricultural goods with share ϕ, the total agricultural and non-agricultural expenditures equal

$$X_r^A = \vartheta_r^A E_r + \phi p_r I_r^D, \quad X_r^{NA} = (1-\vartheta_r^A)E_r + (1-\phi)p_r I_r^D \tag{10}$$

where E_r is the total consumer expenditure in a region and I_r^D the total investment in deforestation. Because of the CES preferences between agricultural goods, the expenditure in agricultural good k equals $X_r^{Ak} = X_r^A \left(\frac{p_r^{Ak}}{p_r^A}\right)^{1-\theta}$. Finally, the total consumer expenditure equals the total income, labour income plus land rental rate payments, net of deforestation investments,

$$E_r = \overline{y}_r^L L_r + v_r T_r^A - p_r I_r^D.$$

where $\overline{y}_r^L$ is the average wage income in region r across all worker, equal to $s_r^A \overline{y}_r^{LA} + (1 - s_r^A)\overline{y}_r^{LNA}$.

Equilibrium definition

Consider the economy described above. Let the initial agricultural land area in each region $\{T_{r0}^A\}_r$, the initial level of area under terrestrial natural ecosystems $\{T_{r0}^N\}_r$, and the distribution of workers across space $\{N_r\}_r$ be given as exogenous. A competitive equilibrium is a set of prices $\{p_r^s\}_{r,s}$, wages $\{w_r^s\}_r$, land rental rates $\{v_r\}_r$, occupational choices $\{N_r^s\}_{r,s}$, regional deforestation levels $\{T_r^D\}_r$, and regional expenditure shares $\{\vartheta_r^A\}_r$ such that:

1. consumers' choices maximize utility (equation (42));
2. the demand for regional varieties follows equations (8);
3. firms' factor demands maximize firms' profits;
4. marginal product of labour is equalised across sectors

5. local markets clear and there is trade balance (9).

5 Calibration and model inversion

In order to use this theoretical model to inform the magnitude of leakage in Brazil, we apply two data-driven strategies. First, in 5.1, we calibrate the parameters of the model through empirical analyses that are consistent with the model structure but do not rely on its equilibrium solution. [27]. Second, in 5.2, we invert the model to structurally estimate the main regional fundamentals - the total factor productivity of the various economic activities, including deforestation, and the amenities that rationalise observed migration rates. This estimation relies on the equilibrium equations of the model matched with selected moments observed in the data. In appendix section D.6, we show the correlation of the data with model outcomes for some non-targeted moments.

5.1 Calibration of model parameters

Table 5 summarises the calibration of the various structural parameters of the model. All parameters are either out-of-model estimates, or set exogenously from similar exercises in the literature. This section is composed of five parts. It begins by describing the calibration of the parameters governing the aggregate deforestation function: how the deforestation production function responds to scale within a year (δ), how the total factor productivity of deforestation decreases as the remaining forest area in a region decreases (ψ), and the rate at which forests regenerate (ρ). Second, it describes the calibration of parameters governing the production of final goods: the parameters governing the joint distribution of the workers' productivity in agriculture and non-agriculture (χ_A, χ_{NA}, ι), and the land shares of the various agricultural activities (α_k). Third, it describes the calibration of the PIGL preference parameters for the consumption of final agricultural and non-agricultural goods. Of these, we take two from the literature, and calibrate the "Engel elasticity" (η) from consumer expenditure survey data. Fourth, it derives the gravity equation of migration flows and shows how it is used to calibrate the bilateral migration costs (μ_d^o) and the dispersion of idiosyncratic taste for different locations (ϵ). Fifth and last, it describes the gravity equation governing trade flows and uses its structure, alongside state-level trade flows from 1999 and 2017 to estimate the distance-elasticity of trade costs (κ).

[27]The literature considers this type of exercise as an out-of-model estimation, even though it partially relies on the model, for example, to impute yearly regional land prices given that these data do not exist

Table 5: Summary of structural parameters calibration

Parameter		**Value**	**Source/Method**
	Deforestation Function		
δ	Deforestation returns to scale	0.5	Two-way fixed effect of deforestation on land prices
ψ	Natural area elasticity of deforestation TFP to	0.32	Regression derived from steady-state deforestation
ρ	Forest regrowth rate	0.01	Observed reforestation rates
	Final Goods Production Functions		
$\{\alpha_k\}_k$	Land share in ag. activities	(0.36;0.54;0.71)	From 2006 ag. census
χ_A, χ_{NA}, ι	Workers' sectoral productivity shocks distribution	(2;1.6;12.8)	Alvarez (2020)
	PIGL preference parameters		
ϕ	Ag. share in price index	0.1	Eckert and Peters (2022)
ν	PIGL Preference parameter	0.5	Eckert and Peters (2022)
η	Engel elasticity	0.506	Expenditure Survey Data (2017/18)
	Elasticities of substitution		
σ	Between origins	9	Eckert and Peters (2022)
θ	Between ag. goods	2	Costinot et al. (2016), Dominguez-Iino (2023)
	Trade and Migration parameters		
$\{\mu_d^o\}_{o,d}$	Bilateral migration utilities	residuals	Migration flows 2005-2010
ϵ	Dispersion of tastes	1.25	Migration flows and incomes from 2010 census
κ	Trade costs distance elasicity.	0.11	Gravity equation of trade flows
	Other Parameters		
β	Discount rate	0.9	NA

5.1.1 Deforestation parameters

Returns to scale: δ For the estimation of the parameter δ from the Cobb-Douglas deforestation production function, we rely on the fact that the supply-elasticity of new agricultural land or the deforestation elasticity, as it is sometimes referred to in the literature, is $\frac{\delta}{1-\delta}$. Recall that the optimal deforestation level T_{rt}^D (from the perspective of the deforesters) given land price q_{rt}, price index p_{rt}, and aggregate deforestation TFP $Z_r^D t$ is equal to:

$$T_{rt}^D = (Z_{rt}^D)^{\frac{1}{1-\delta}} \left(\frac{\delta q_{rt}}{p_{rt}}\right)^{\frac{\delta}{1-\delta}}.$$

Taking logarithms, the equation becomes:

$$\log(T_{rt}^D) = \frac{1}{1-\delta}\log(Z_{rt}^D \delta^\delta) + \frac{\delta}{1-\delta}\log q_{rt} - \frac{\delta}{1-\delta}\log p_{rt}. \tag{11}$$

From this equation, we observe deforestation levels, T_r^D, and we can approximate yearly land rental rates v_{rt} (assumed to have a simple linear relationship to land prices so that $q_{rt} = \frac{1}{1-\beta(1-\rho)} v_{rt}$) from the yearly data on agricultural revenues described in section 2.3 and the Cobb-Douglas production function assumption[28]. Ideally we would like to estimate the coefficient on $\log(v_{rt})$ from shocks that come exclusively from changes in the demand for land and not from changes in the costs of deforestation. Given the fact that this is an equilibrium equation, simultaneity is a concern. Just as increases in the demand for land increase both land prices and deforestation in equilibrium, increases in the supply of new agricultural land (for example due to less strict conservation policies) increase deforestation but lower land prices. In the absence of an instrument that proxies for an exogenous shock to supply or demand separately, we run a regression with time and municipality fixed effects as in the equation below:

$$\boxed{\log(T_{rt}^D) = \alpha_r^1 + \alpha_t^2 + \frac{\delta}{1-\delta}\log v_{rt} + \epsilon_{rt}}. \tag{12}$$

The municipality and year fixed effects help to control for constant differences between municipalities and common macroeconomic shocks to anti-deforestation policy and to agricultural markets that are common to all regions. Panels (1) and (2) of Table 6 show the results of this two-way fixed effects regression without weights and weighting by the total area in agriculture. In panels (3) and (4), we instrument for $\log v_{rt}$ with $\log v_{rt-1}$ and $\log v_{rt-2}$, following Anderson and Hsiao (1982). This helps us to lessen simultaneity concerns. Another reason why we may be less worried about simultaneity in this context relative to standard

[28] In each region, the land rental rate is calculated as $v_{rt} = \left(\sum_k \alpha_k \text{Revenue}_k\right)/\text{Area Agri}_{rt}$ for all k

Table 6: Estimation of δ

	Outcome: log(Deforestation)			
	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
$\log(v_r)$	0.391***	0.253***	0.817***	1.065***
	[0.025]	[0.038]	[0.165]	[0.283]
Mun. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Instrument	-	-	First Difference	First Difference
Weight	None	Agri. Area	None	Agri. Area
R2	0.240	0.346	0.002	-0.001
Observations	89072	89072	77938	77938

Note: This table shows the results of a two-way fixed effects regression of the log of deforestation on the log of estimated land rental rates at the municipality level, (12). The coefficient estimate displayed is $\frac{\delta}{1-\delta}$, where δ governs the returns to scale of the deforestation production function. Columns (1) and (2) show the results of the OLS regression and columns (3) and (4) show the results of the IV regression that instruments for land rental rates with its lagged values following Anderson and Hsiao (1982). Columns (1) and (3) weigh all municipalities equally and columns (2) and (4) weigh them by their total area in agricultural use. Standard errors in parenthesis. *p<0.1, **p<0.05, *** p<0.01.

supply-elasticity estimations, is that land accumulates over time. Hence, the yearly rate of deforestation is likely to be too small to have a significant effect on the price of agricultural land in a region, so that the movements observed in agricultural land prices are most likely due to changes in the demand for land. The resulting elasticities of deforestation range between 0.25 and 1.1, implying δ between 0.2 and 0.52. For the main specification of the model, δ is set to be 0.5. This is for two reasons. First, because it is in line with a deforestation elasticity of 1, which is very close to what is calibrated in Farrokhi et al. (2024) for global deforestation (0.9) and to the crop-price elasticity of pan-tropical deforestation in Berman et al. (2023). Moreover, we choose to err on the side of overestimating δ, which will in turn overestimate leakage. This is because, as we shall see in the next chapter, we find relatively low rates of leakage, and therefore we want to put their seemingly small magnitude to test.

Returns to unprotected forest left: ψ The second parameter of interest governing the deforestation technology is ψ. This parameter dictates how the productivity of aggregate deforestation goes down as there is less area left in unprotected natural ecosystems. While $\delta < 1$ (yearly decreasing returns to scale) makes it so that it is optimal to space out deforestation over time because each additional hectare is harder to cut down in a given year, $\psi > 0$ makes it so that the costs of deforesting the area of forest over the same extension of time is higher when there is less forest left. This could be either because the forest that is easier to cut down is chosen first or because the value of the standing forest, and hence the opportunity cost of deforestation, increases as it becomes scarcer. ψ can be calibrated in two ways, both of which deliver similar results. One requires doing the model inversion first and estimating deforestation TFPs Z_{rt}^D for each region r in each year t and then regressing that on the forest area left in each micro-region in a log-log regression. This will be described in the next section. The out-of-model alternative to calibrate ψ is to derive it from the steady-state condition that would make the amount of forest in a region constant by equating forest loss and forest regrowth rates,

$$T_{r,ss}^D = \rho T_{r,ss}^A.$$

Substituting in the optimal level of deforestation and $Z_{r,ss}^D = \overline{Z}_{r,ss}^D \left(T_{r,ss}^F\right)^{\psi}$, we can derive an equation that relates the ratio of area in forest over the area in agricultural use on the left hand side to the total area in forest to the power of $1 - \psi/(1-\delta)$ on the right hand side.

$$\frac{T_{r,ss}^F}{T_{r,ss}^A} = \rho(\overline{Z}_{r,ss}^D)^{\frac{1}{\delta-1}} \delta^{\frac{\delta}{\delta-1}} \left(\frac{q_{r,ss}}{p_{r,ss}}\right)^{\frac{\delta}{\delta-1}} (T_r^F)^{1-\frac{\psi}{1-\delta}}$$

Take logs

$$\begin{aligned} \log\left(\frac{T_{r,ss}^F}{T_{r,ss}^A}\right) =& \log\left(\rho(\overline{Z}_{r,ss}^D)^{\frac{1}{\delta-1}} \delta^{\frac{\delta}{\delta-1}}\right) \\ & - \frac{\delta}{1-\delta} \log\left(\frac{q_{r,ss}}{p_{r,ss}}\right) \\ & + \left(1 - \frac{\psi}{1-\delta}\right) \log(T_{r,ss}^F) \end{aligned} \tag{13}$$

This is governing the way in which the ratio of forest to agricultural depends on scale in steady state. More precisely, how regions with larger steady-state area in forest have a higher (if $\psi < 1-\delta$; lower if $\psi > 1-\delta$) fraction of their area in forest relative to agricultural use. If $\psi = 0$, the optimal amount of agricultural area (cumulative deforestation) would be completely independent on the available forest (assuming that we only have interior solution), and hence the ratio of forest area to agricultural area would increase proportionally to forest area (with elasticity 1). For conciseness let us refer to $1 - \psi/(1-\delta)$ as the long-run scale elasticity of forest cover, since it dictates how the total area in forest cover relates to the relative area in forest cover. As ψ increases, this elasticity decreases: having a larger area in forest is associated with having a lower relative forest cover. This is because ψ dictates how the yearly deforestation productivity increases with the extent of forest left, and hence with scale. The parameter δ is a compounding force influencing the long-run scale elasticity of forest cover. As δ increases, deforestation has more strongly decreasing returns to scale, and hence a larger area is harder to convert to agriculture, so that the steady state agricultural area becomes relatively smaller as a function of scale. If $\psi > 1-\delta$ this long-run scale elasticity of forest cover becomes negative, so that larger regions would end up with higher fractions in agricultural land relative to smaller regions. We consider this scenario implausible. Given that the only variables in the equation above that we observe are v_{rt} (proportional to q_{rt}), T^F_{rt}, and T^A_{rt}, we run the regression below to estimate $\delta/(1-\delta)$ and $1-\psi/(1-\delta)$ simultaneously, and then use this estimated δ (or the chosen 0.5) to back out ψ. The regression equation is

$$\boxed{\log\left(\frac{T^F_{rt}}{T^A_{rt}}\right) = \alpha_{s(r)t} - \frac{\delta}{1-\delta}\log(v_{rt}) + \left(1-\frac{\psi}{1-\delta}\right)\log(T^F_{rt}) + \epsilon_{rt}}, \tag{14}$$

where $s(r)$ is the state of region r. We control for state-year fixed effects to look only at within state-year differences in forest-to-agricultural areas. The source of variation that we want to use is cross-sectional rather than a diff-in-diff because we are interested in the long-run differences across regions with differences sizes. Since regions with high deforestation are less likely to have reached their steady state, in column (3) we consider exclusively those regions were deforestation rates are below the regrowth rate, i.e. 1% of the agricultural area. The results, shown in Table 7, are consistent with a δ between 0.26 and 0.29. Taking this value, we get a ψ between 0.3 and 0.32. If instead we took $\delta = 0.5$ we get ψ between 0.17 and 0.22. In order to err on the side of underestimating leakage, again, we opt for a ψ on the larger side. This is also more consistent with the results of the model-based method.

Regrowth rate: ρ The regrowth rate ρ is calculated from MapBiomas forest transitions data on growth of secondary forest divided by land under anthropic use in the previous year. Calculating an average regrowth rate over the whole of Brazil for the model period (2002-2019), we get 1%, ranging between 0.81% (in 2019) and 1.1% (in 2017), with a slightly decreasing trend over time. We consider ρ to be the same for all regions, but in reality it has significant spatial variation. The average micro-region has a regrowth rate of 1.5%, the median micro-region of 0.8%.

5.2 Model inversion

In order to invert the model and back out the total factor productivities of each sector and the deforestation productivity (Z^{Ak}_{rt}, Z^{NA}_{rt}, Z^{D}_{rt}) we assume that each year in the period 2003-2019 the economy is in equilibrium as described above and we use data on some observed

Table 7: Estimation of ψ

	Outcome: log((Natural Area)/(Agri. Area))		
	(1)	(2)	(3)
log(Unprotected Natural Area)	0.668***	0.589***	0.571***
	[0.004]	[0.004]	[0.004]
$\log(v_r)$		-0.419***	-0.357***
		[0.005]	[0.007]
State X Year FE	Yes	Yes	Yes
Weight	Agri. Area	Agri. Area	Agri. Area
Sample			Low deforest.
R2	0.735	0.793	0.805
Observations	28244	27875	16899

Note: This table shows the results of a regression of the log of the ratio of land in forest over land in agriculture on the log of the total area in forest at the municipality-year level, following (13). The first coefficient estimate displayed is $1 - \frac{\psi}{1-\delta}$, where ψ governs the "returns to total unprotected forest left" and δ governs the returns to scale of the deforestation production function. All columns controls for state-year fixed effects and weigh municipalities by agricultural area. Column (1) does not have any additional controls. Columns (2) and (3) control for the log of the estimated rental rate of agricultural land. Column (3) restricts he sample to observations with less than 1 square kilometer of forest loss so that it is more plausibly looking at a steady state. Standard errors in parenthesis. *p<0.1, **p<0.05, *** p<0.01.

features. First, we use data on the endowments that are treated as exogenous within each equilibrium. That is, working population, land already in agriculture, and land in natural ecosystems. Second, we use data on the following equilibrium quantities in each region for that year: (i) the total amount of deforestation, T^D_{rt}, (ii) the agricultural labour share (s^A_{rt}), (iii) the share of agricultural land in each land use (T^{Ak}_{rt}), and (iv) agricultural revenues ($p^{Akr}_t Y^{Ak}_{rt}$). Through the algorithm described in appendix section C, we back out the TFPs. the residential amenities are assumed to be constant and are backed out from equation 45 (i) the observed level of consumption utilities V_d, the destination fixed effects estimated from 44, and the calibrated ϵ.

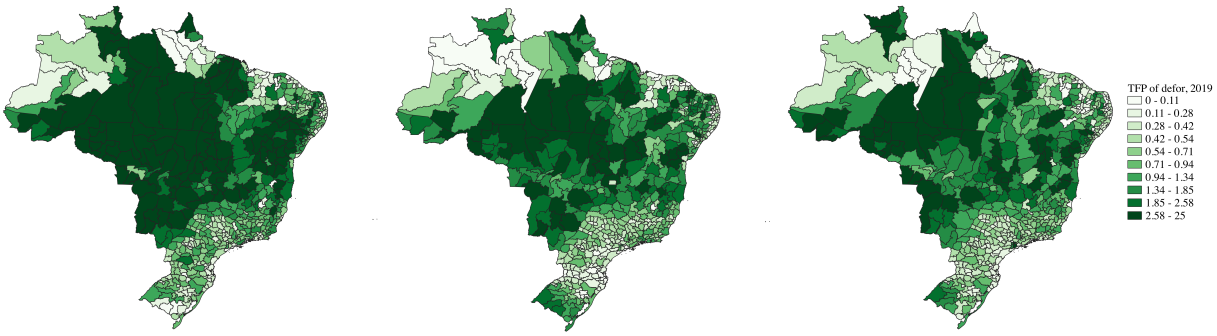
The maps below show the spatial distribution of the regional fundamentals and how they change over the 2003-2019 period.

Correlation between fundamentals and deforestation levels

In this theoretical framework, the deforestation is rationalised by the combination of two market forces: the demand for agricultural land and the supply of deforestation. The supply-side regional fundamental governing deforestation is Z^D_r. The demand for agricultural land is given, in turn, by the equilibrium in the market for agricultural goods. From the agricul-

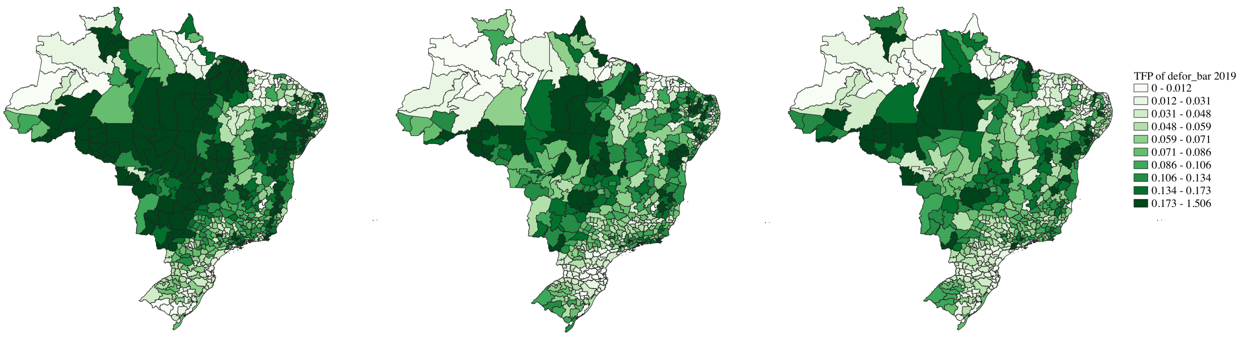
Figure 11: Estimated Deforestation TFPs

TFP of deforestation, total



(a) 2003 (b) 2011 (c) 2019

TFP of deforestation, residual

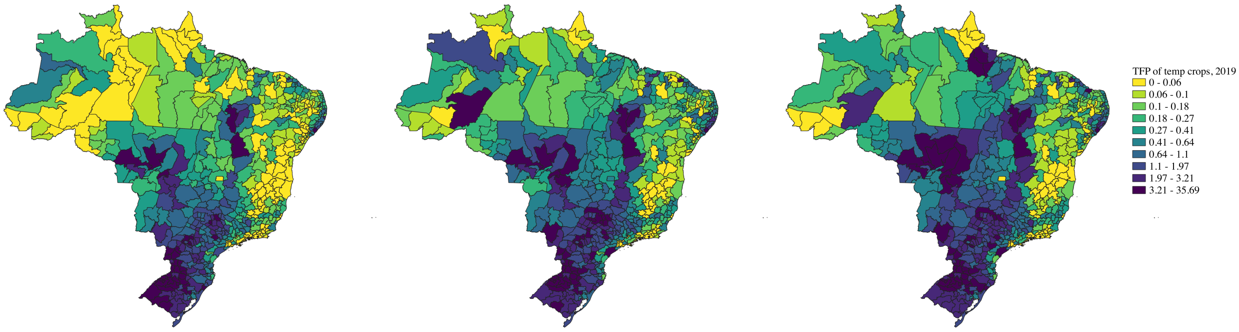


(d) 2003 (e) 2011 (f) 2019

Note: These maps illustrate the spatial distribution of the deforestation productivities across Brazil for the years 2003, 2011, and 2019. The maps at the top, (a)-(c), show the total deforestation TFP $Z_{rt}^D = \overline{Z}_{rt}^D (T_{rt}^F)^\psi$ which includes the dependence of the TFP on unprotected forest area. The legend is consistent across these three maps. The maps at the bottom, (d)-(f), show the residual TFP after taking out the dependence on unprotected forest area left, $\overline{Z}_{rt}^D$. The legend is consistent across these three maps.

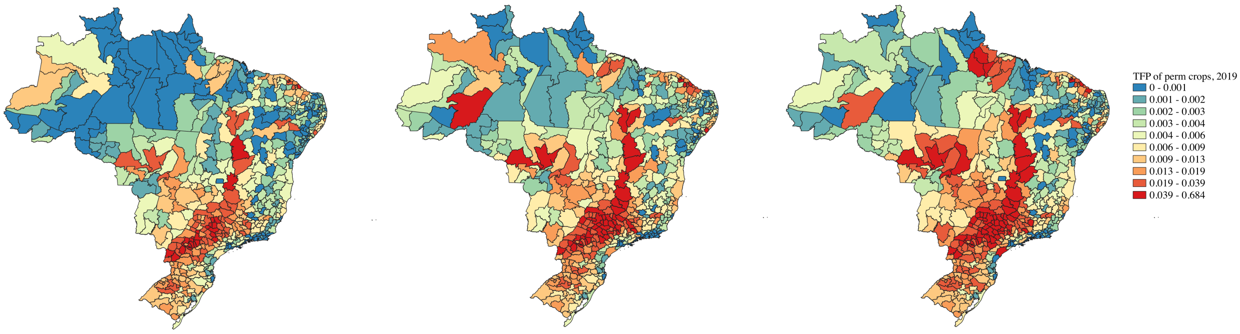
Figure 12: Estimated Agricultural TFPs, by activity

TFP of temporary crops



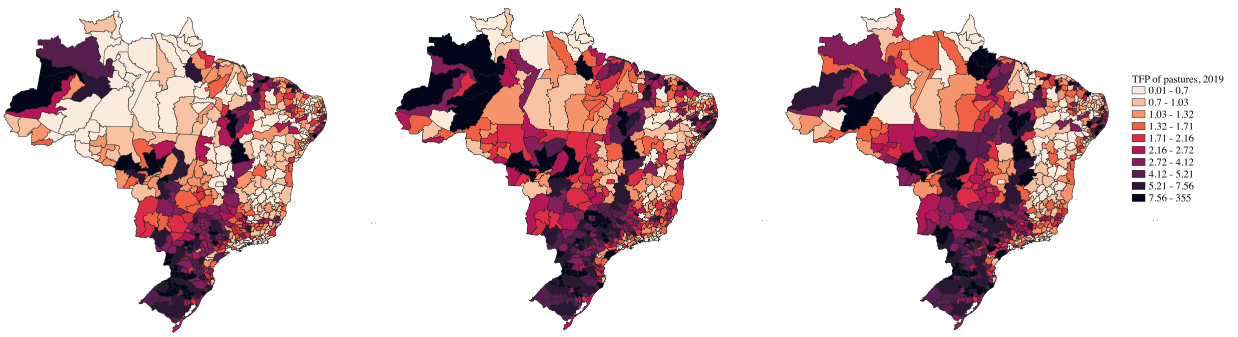
(a) 2003 (b) 2011 (c) 2019

TFP of permanent crops



(d) 2003 (e) 2011 (f) 2019

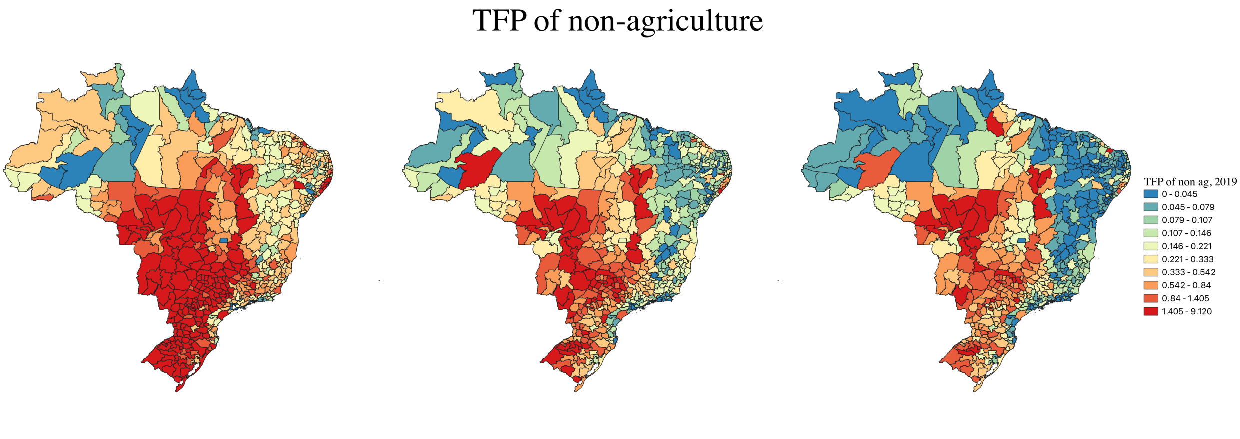
TFP of pastures



(g) 2003 (h) 2011 (i) 2019

Note: These maps show the spatial distribution of the agricultural productivities of the three agricultural sectors considered (permanent crops, temporary crops, and pastures) across Brazil for the years 2003, 2011, and 2019. The estimation of each year's productivities is done through an exact inversion of the model in that year, assuming equilibrium conditions.

Figure 13: Estimated Non Agricultural TFPs



(a) 2003

(b) 2011

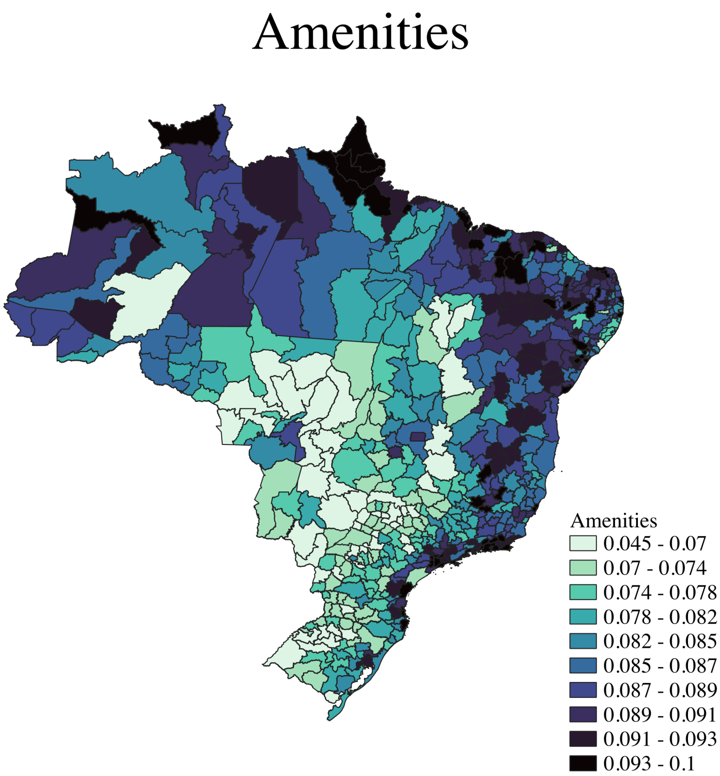
(c) 2019

Note: These maps show the spatial distribution of the agricultural productivities of the non-agricultural productivity across Brazil for the years 2003, 2011, and 2019. The estimation of each year's productivities is done through an exact inversion of the model in that year that assumes equilibrium conditions.

tural goods supply side, we expect to see more deforestation in regions which have higher agricultural TFPs, especially for the land-intensive agricultural activities (i.e. cattle grazing). From the demand side, the regions that have higher market access should experience greater demand for agricultural goods, and hence for agricultural land, as discussed in Donaldson and Hornbeck (2016).[29] In summary, there are three sets of regional fundamentals driving the spatial allocation of deforestation, each of which have different implications for the level of leakage: (1) the deforestation TFP, (2) the TFP of agricultural activities, especially the most land-intensive ones, and (3) market access. Table 8 presents the estimated coefficients of a simple regression of the baseline levels of (log) deforestation on the (log) productivities of various sectors and the log of a measure of market access approximated by $MA_r \approx \sum_d (\tau_d^r)^{\sigma-1} L_d$ as in Donaldson and Hornbeck (2016). In columns (1) and (2), which do not include the deforestation TFP, the coefficients go in the opposite direction as we would expect them to affect deforestation. Column (3) shows that a large share of the variation in deforestation levels is explained by the deforestation TFP, the immobile factor that is shocked for the counterfactual policy simulation ($R^2 = 0.811$). Column (4) shows that deforestation is well explained ($R^2 = 0.987$) and that once the deforestation TFP is added to the regression in column (2) all the coefficients flip sign to align with the model-based predictions. That is, deforestation increases with: (i) higher agricultural productivity, (ii)

[29] Here σ corresponds to the elasticity of substitution between different regional varieties of the final goods.

Figure 14: Estimated Amenities



Note: These maps show the spatial distribution of the residential amenities across Brazil for the years 2003, 2011, and 2019. The estimation is done through an exact inversion of the model, which rationalises observed migration flows given estimated bilateral migration costs and region-specific yearly utilities.

lower non-agricultural productivity, and (iii) higher market access.

Table 8: Correlates of observed deforestation

	Outcome: log-observed yearly deforestation			
	(1)	(2)	(3)	(4)
(log) temp. crops TFP	-0.54***	-0.21***		0.10***
	[0.04]	[0.03]		[0.00]
(log) perm. crops TFP	-0.39***	0.03		-0.00
	[0.03]	[0.03]		[0.00]
(log) pasture TFP	-0.16***	-0.61***		1.14***
	[0.05]	[0.04]		[0.01]
(log) non-ag TFP	1.08***	0.67***		-0.38***
	[0.03]	[0.03]		[0.00]
(log) Market acces		-1.19***		0.26***
		[0.02]		[0.00]
(log) Deforestation TFP			1.39***	1.90***
			[0.01]	[0.00]
R^2	0.122	0.306	0.811	0.987
Dep. Var. Mean	2.69	2.69	2.69	2.69
Dep. Var. SD	1.95	1.95	1.95	1.95
Observations	8587	8587	8587	8587

Note: This table displays the results of four OLS regressions at the micro-region-year level. The dependent variable is the log of the yearly deforestation rate. The regressors are a variety of combinations of model-estimated regional fundamentals (all in logarithms). Column (1) includes the productivities of all sectors producing final goods. Column (2) includes market access too. In columns (1) and (2) the coefficients go in the opposite direction as we would expect them to affect deforestation. Column (3) regresses log deforestation only on the log of the estimated deforestation TFP and column (4) includes all the regressors in column (2) and the estimated deforestation TFP.

6 Counterfactual Analysis

The theoretical framework developed in the previous section allows us to simulate counterfactual scenarios of local deforestation policy, and understand how deforestation would have evolved in general equilibrium in these alternative scenarios. In particular, we can apply the model to analyse the national impact of the two types of local, yet large scale, anti-deforestation policies implemented by the Brazilian government over the past decades (Priority List and Protected Areas), taking into account general equilibrium effects.

6.1 Defining counterfactuals and leakage

For each of the two policies, we simulate two counterfactual scenarios for the evolution of nation-wide deforestation between the years 2003 and 2018.

> **Counterfactual A: No policy** – a scenario in which, between 2003 and 2018, the policy was never enacted.
>
> **Counterfactual B: Policy, no leakage** – a scenario in which, between 2003 and 2018, the policy was implemented, but it has no general equilibrium effects

The difference between counterfactual A and the observed evolution of deforestation measures the overall effect of the policy, including both the direct effect via banned deforestation in targeted areas, and the indirect effect via potential leakage to non-targeted areas. The difference between the observed evolution of deforestation and counterfactual B measures the amount of leakage caused by the localised policies. The difference between counterfactuals A and B measures the total effect of the localised policies under no deforestation leakage, i.e. only considering the direct effect via banned deforestation in targeted areas.

For each of the two policies, we construct the counterfactuals as follows: First, we calibrate the baseline regional fundamentals $\{Z_{rt}^s,\, B_{rt}\}$ to fit the observed deforestation between the years of 2003 and 2018. We construct $(Z_{rt}^D)^{nopolicy}$, the deforestation productivity of each region in a counterfactual scenario where the policy was not implemented as described in the subsections 6.1 and 6.1 below.

For counterfactual A, we simulate total land cleared for agriculture in each year between 2003 and 2018, solving for the optimal deforestation level $(T_{rt}^D)^{nopolicy}$ according to Equation 6 using the calculated regional deforestation productivity $(Z_{rt}^D)^{nopolicy}$. Total agricultural land at each period is then given by equation 15.

$$(T_{rt}^{A})^{nopolicy} = (1-\rho)(T_{rt-1}^{A})^{nopolicy} + (T_{rt}^{D})^{nopolicy} \tag{15}$$

For counterfactual B, we calculate a "no leakage" scenario that has the implied prices coming from counterfactual A (i.e. no-policy prices), and baseline region deforestation productivities estimated through the model Z_r^D (with policy). Fixing the prices under the no-policy scenario effectively shuts down the channel through which deforestation could leak to other areas, as both labour market and goods market relocation mechanisms operate through price channels.

$$(T_r^D)^{noleakage} = \left(\delta \frac{(q_r)^{nopolicy}}{(p_r)^{nopolicy}}\right)^{\frac{\delta}{1-\delta}} (Z_r^D)^{\frac{1}{1-\delta}} \tag{16}$$

No Priority List deforestation productivities

In order to estimate the counterfactual deforestation productivities of regions in the Priority List, we do the following. First, we estimate the effect of the policy on the values of Z_{rt}^D obtained from the model inversion. The preferred model is a following Poisson quasi-maximum likelihood model with region and time fixed effects, as shown below

$$\mathbb{E}(\overline{Z}_{rt}^{D}|r, t, \text{Priority}_{rt}) = \exp(\alpha_r + \delta_t + \beta \text{Priority}_{rt} + \epsilon_{rt})$$

Having estimated β, we construct a no-priority-list $(\overline{Z}_{rt}^{D})^{nopolicy}$ that equals

$$(\overline{Z}_{rt}^{D})^{nopolicy} = \overline{Z}_{rt}^{D} / \exp(\widehat{\beta}). \tag{17}$$

Using this new productivity of deforestation, we simulate the model forward for 17 periods starting in 2003. The resulting timeseries corresponds to counterfactual A for the Priority List. The overall deforestation productivities $(Z_{rt}^D)^{nopolicy}$ will be different both because of the changes in $\overline{Z}_{rt}^{D}$ in Priority List regions that are external to the simulation and because of the endogenous changes in T_{rt}^F that will happen in all regions. In particular, Priority List municipalities will have more remaining areas in forest, and the rest will have less.

$$(Z_{rt}^D)^{nopolicy} = (\overline{Z}_{rt}^{D})^{nopolicy}((T_{rt}^F)^{nopolicy})^{\psi} \tag{18}$$

Figure 15 below shows these changes in deforestation productivities. In panel (a) we plot the change in the yearly average over all regions, and in panel (b) we plot three maps, for 2008, 2011, and 2019, of the resulting changes in deforestation productivity Z_r^D of each region.

No Protected Areas deforestation productivities

The procedure to estimate the counterfactual deforestation productivities as if there were no new protected areas established between 2003 and 2008 is as follows. We assume that part of the deforestation productivity that changes is not $\overline{Z}_{rt}^D$ but T_{rt}^F, the area of r under unprotected forest. Given the extremely low rates of deforestation inside protected areas, we assume that they have perfect enforcement and that none of them can be converted to agricultural. Let T_{rt}^P be the area of region r that gets protected in year t. In order to simulate the reversal of new Protected Areas, we increase the area in available land for deforestation by T_{rt}^P. So that,

$$(Z_{rt}^D)^{nopolicy} = \overline{Z}_{rt}^D((T_{rt}^F)^{nopolicy} + T_{rt}^P)^{\psi}, \tag{19}$$

where $(T_{rt}^F)^{nopolicy}$ is the remaining observed area of unprotected forest in region r at time t resulting from the simulation of counterfactuals with no new protected areas in previous periods. This is an iterative definition, as $(T_{rt}^F)^{nopolicy}$ depends on $(Z_{r\tau}^D)^{nopolicy}$ for $\tau < t$.

6.2 Counterfactual deforestation and leakage

Now we turn to the results of the counterfactual simulations on the levels of deforestation. Given the counterfactual levels of deforestation for counterfactuals A, $(T_{rt}^D)^{nopolicy}$, and B, $(T_{rt}^D)^{policy,noleakage}$, we can also calculate the total percentage of deforestation reduction that is undone by general equilibrium effects:

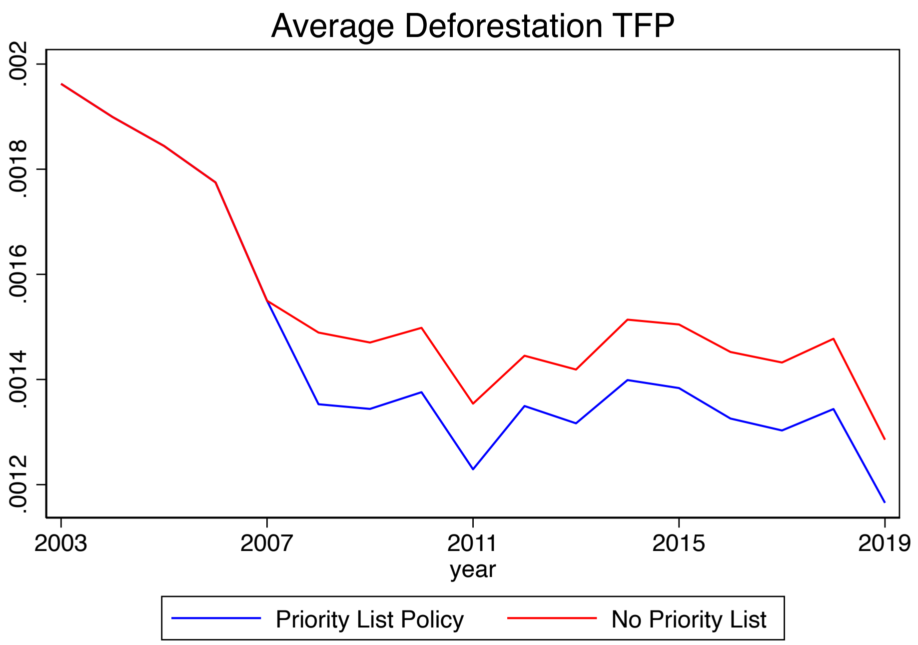
$$\text{Leakage}_t = \sum_r \Bigg(\underbrace{(T_{rt}^D)^{policy}}_{\text{Data}} - \underbrace{(T_{rt}^D)^{noleakage}}_{\text{Counterfactual B}} \Bigg) \Big/ \Bigg(\underbrace{(T_{rt}^D)^{nopolicy}}_{\text{Counterfactual A}} - \underbrace{(T_{rt}^D)^{noleakage}}_{\text{Counterfactual B}} \Bigg) \tag{20}$$

I will then convert the rates of deforestation from surface area to carbon emissions (in C tonnes) using data on the heterogeneous carbon density of the natural ecosystems of the various regions.

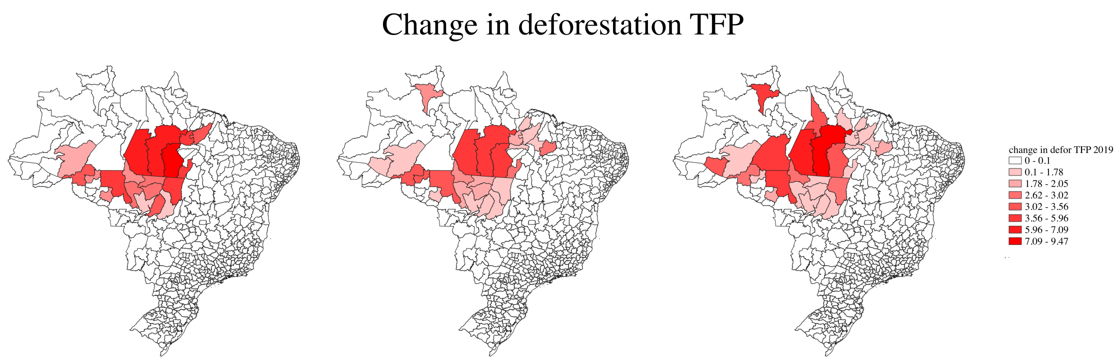
Priority List

Figure 17 shows the evolution in total observed deforestation across Brazil, as well as the results from simulating counterfactuals A and B for the Priority List Policy. The line in

Figure 15: Changes in deforestation productivity: Priority List



(a) Changes in average deforestation productivity

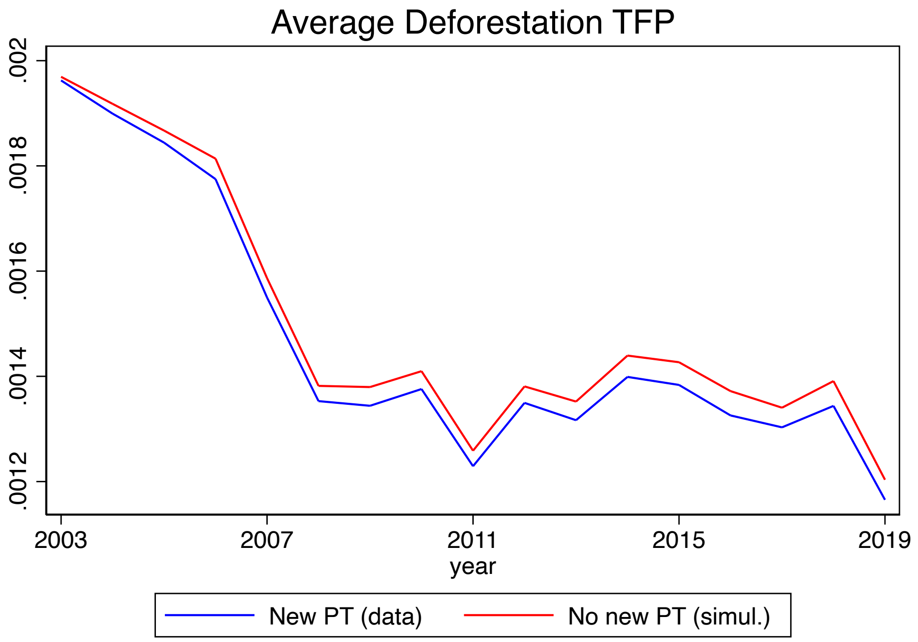


(a) 2008 (b) 2013 (c) 2019

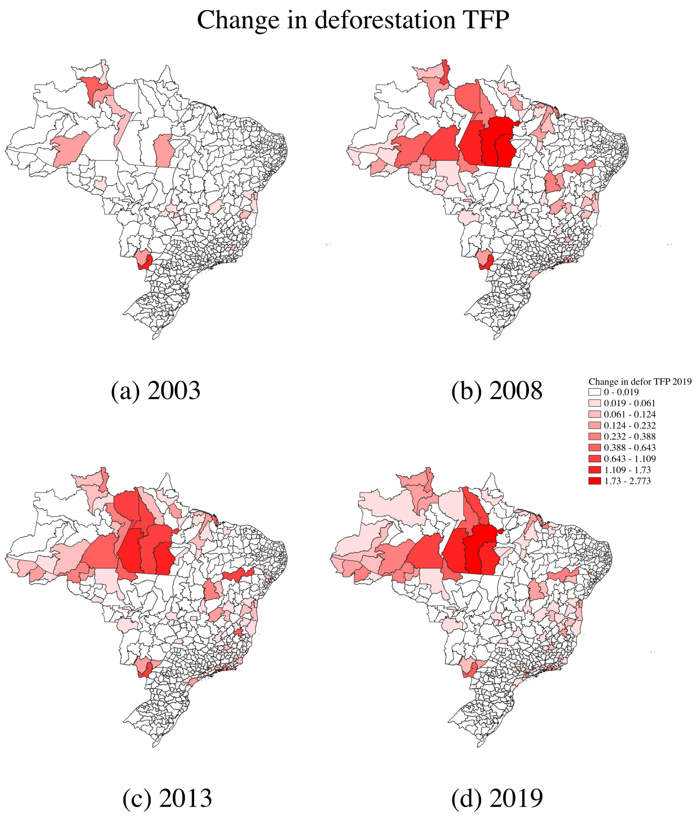
(b) Map of changes in deforestation productivity

Note: This figure illustrates the difference in estimated deforestation TFPs between (i) the estimated value from the inversion of the model using observed data, and (ii) the simulated scenario in which there is no Priority List following equations (17) and (18). Panel (a) on top, shows the trends in deforestation TFP Z_{rt}^D for both scenarios over the study period 2003-2019. Panel (b) at the bottom show the spatial distribution of the differences in Z_{rt}^D between scenarios (i) and (ii).

Figure 16: Changes in deforestation productivity: Protected Areas



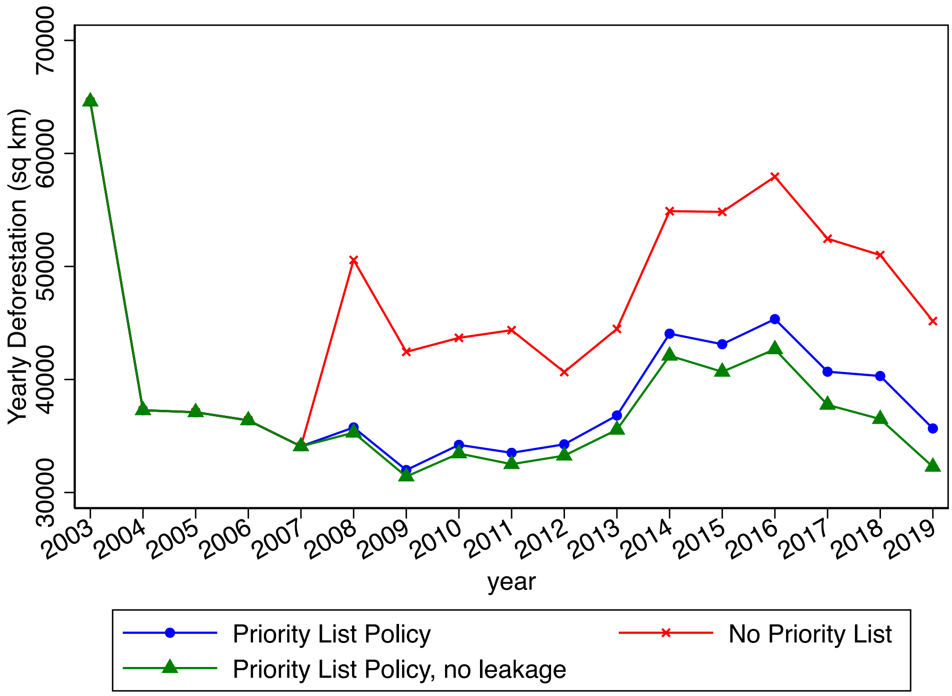
(a) Changes in deforestation productivity: Protected Areas



(b) Map of changes in deforestation productivity

Note: This figure illustrates the difference in estimated deforestation TFPs between (i) the estimated value from the inversion of the model using observed data, and (ii) the simulated scenario in which there are no new Protected Areas from 2003 following equation (19). Panel (a) on top, shows the trends in deforestation TFP Z^D_{rt} for both scenarios over the study period 2003-2019. Panel (b) at the bottom show the spatial distribution of the differences in Z^D_{rt} between scenarios (i) and (ii).

Figure 17: Counterfactual deforestation trends: Priority List

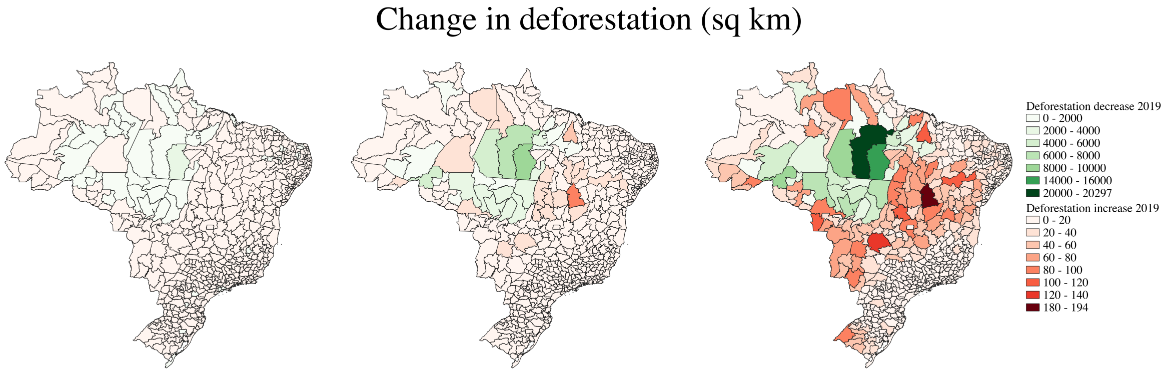


Note: This figure shows the trends in yearly deforestation levels (in thousands of squared kilometers) across Brazil between the years of 2003 and 2019 under counterfactual simulations based on the Priority List policy. The blue curve represents observed deforestation, the red curve represents a counterfactual scenario in which the policy was never implemented, and the green curve represents a counterfactual in which the policy was implemented and GE effects, and hence leakage, are shut down by considering the prices under the no-policy scenario.

blue depicts the reduction in deforestation in the data. That is, in the scenario where the policy is implemented and has GE effects. The line in red shows the reversal of the policy (Counterfactual A), and the line in green shows the rates of the policy without GE effects (Counterfactual B).

Figures 18 and 19 show the differences between observed data and the two counterfactuals. The former shows the overall changes in deforestation between the data and the scenario with no policy. This corresponds to the aggregate effects of the policy combining direct and GE effects. Overall one can see that the microregions that are in the Priority List have substantial decreases in deforestation that are about one order of magnitude greater than those in the non-Priority List regions. In the second set of maps, it can be seen that the price effects on deforestation (difference between the data and counterfactual B) are higher where deforestation productivites are higher. Since the Priority List does not fully ban deforestation, some of the general equilibrium effects, which we still call leakage, are *within*

Figure 18: Counterfactual deforestation maps: Priority List



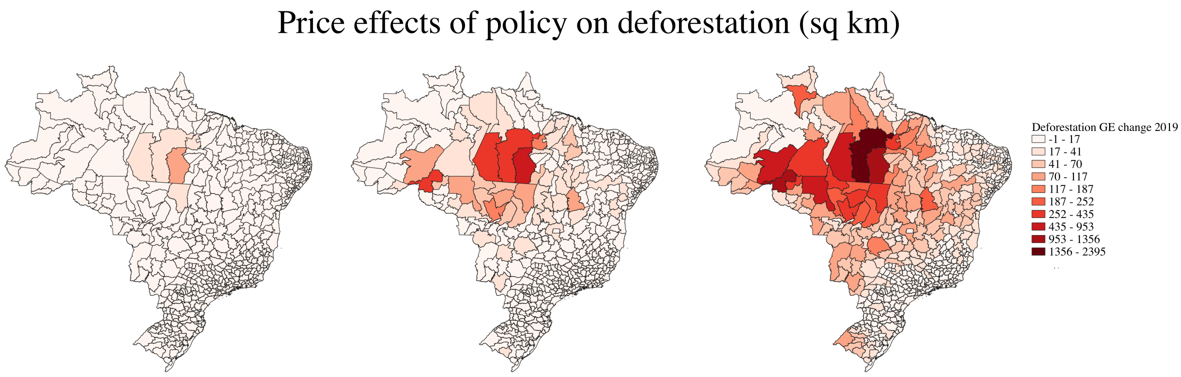
(a) 2008 (b) 2013 (c) 2019

Note: This figure shows the Priority-List-driven changes in cumulative deforestation (in thousands of squared kilometers) across the various microregions of Brazil for years 2008, 2013, and 2019. Specifically, it maps the differences between deforestation in the data (which includes the effect Priority List policy) and the no-policy counterfactual simulation. The regions where the Priority List policy is implemented have some large decreases in deforestation, while the rest of the country has increases, albeit much smaller in magnitude.

priority-listed regions.

Figure 20 illustrates the evolution of the cumulative leakage to non-treated areas expressed as a share of the avoided deforestation, as defined in equation 20. Leakage at the start of the considered period is low, around 3%, but increases gradually over time. By 2019, approximately 15% of the deforestation avoided by the policy in the targeted areas is outdone by general equilibrium effects. About 50% of these general equilibrium effects happen within Priority List regions. In-situ leakage would not cause biases of reduced-form estimates. It would instead be a mechanism that could explain why effects are lower than they might otherwise be if the conservation policy did not make agricultural land scarcer. This means that only about 7% of reductions in deforestation are outdone by displacement to non-Priority List regions. When looking at these results for Carbon emissions rather than total area the size of leakage to non-Priority Listed regions is even smaller, only 3%. This makes sense given that: (i) Priority List regions have the highest productivities of deforestation, even after implementing the policy, and leakage is expected to be higher in places with highest deforestation productivity, (ii) Priority List regions exhibit some of the highest carbon densities. There are regions with higher carbon densities, especially in the northern side of the Amazon River basin, but these are at lower risk due to a combination of lower market access and lower agricultural productivities.

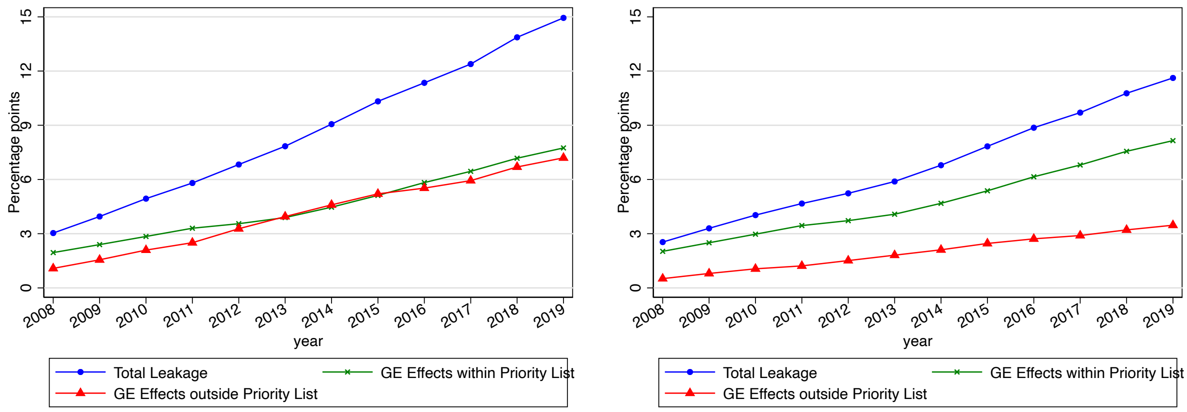
Figure 19: General Equilibrium Effects maps: Priority List



(a) 2008 (b) 2013 (c) 2019

Note: This figure shows the spatial distribution of the part of Priority-List-driven changes in cumulative deforestation (in thousands of squared kilometers) that is due to GE effects. Namely, it is the difference between the scenario with Priority List policy (data) and the scenario with TFPs as in the data, but prices as in the no-policy simulation. The spatial units are the various microregions of Brazil for years 2008, 2013, and 2019. GE effects have consequences in all of Brazil, but they are more pronounced in the Priority Listed micro-regions and their neighbours.

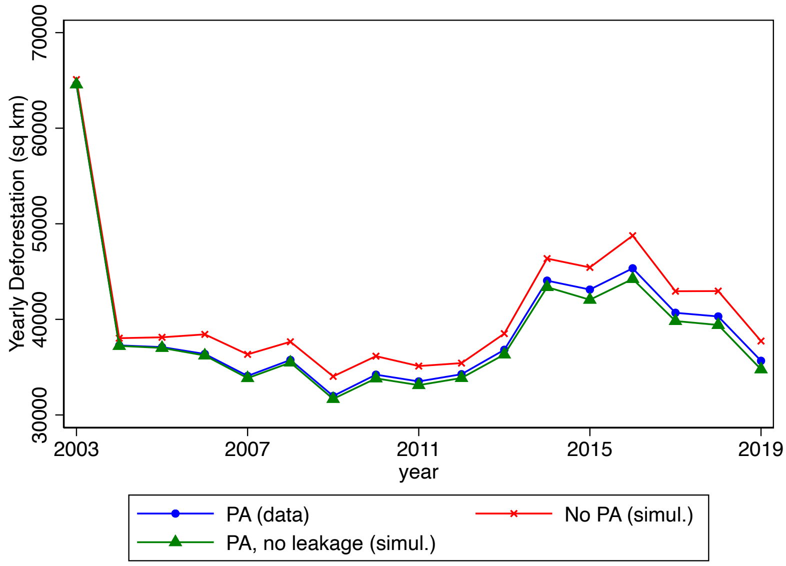
Figure 20: Cumulative leakage: Priority List



(a) Leakage of area deforested (b) Leakage of Carbon emissions

Note: This figure shows the evolution of the leakage of the Priority-List policies over time. The blue line indicates the total % of (cumulative) avoided deforestation that is outdone by increases due to GE effects ("leakage"), following formula (20). Some of the GE effects, however, are experienced within Priority List regions, as shown in map (19) because GE effects counteract deforestation efforts within the targeted region. The green line shows the fraction of this leakage that is due to deforestation reduction in Priority-List regions. The red line shows the fraction of leakage that is "true leakage": that is, % of avoided deforestation outdone be increases in deforestation in no-policy regions. Panel (a) shows leakage in terms of area deforested while panel (b) shows leakage in terms of carbon emissions. Carbon emissions are calculated using the micro-region level average of the carbon density (including both above- and below-ground) of natural ecosystems in 2010.

Figure 21: Counterfactual deforestation trends: Protected Areas



Note: This figure shows the trends in yearly deforestation levels (in thousands of squared kilometers) across Brazil between the years of 2003 and 2019 under counterfactual simulations based on the establishment of Protected Areas. The blue curve represents observed deforestation, the red curve represents a counterfactual scenario in which no new territories are protected from 2003, and the green curve represents a counterfactual in which new Protected Areas are established and GE effects, and hence leakage, are shut down by considering the prices under the no-policy scenario.

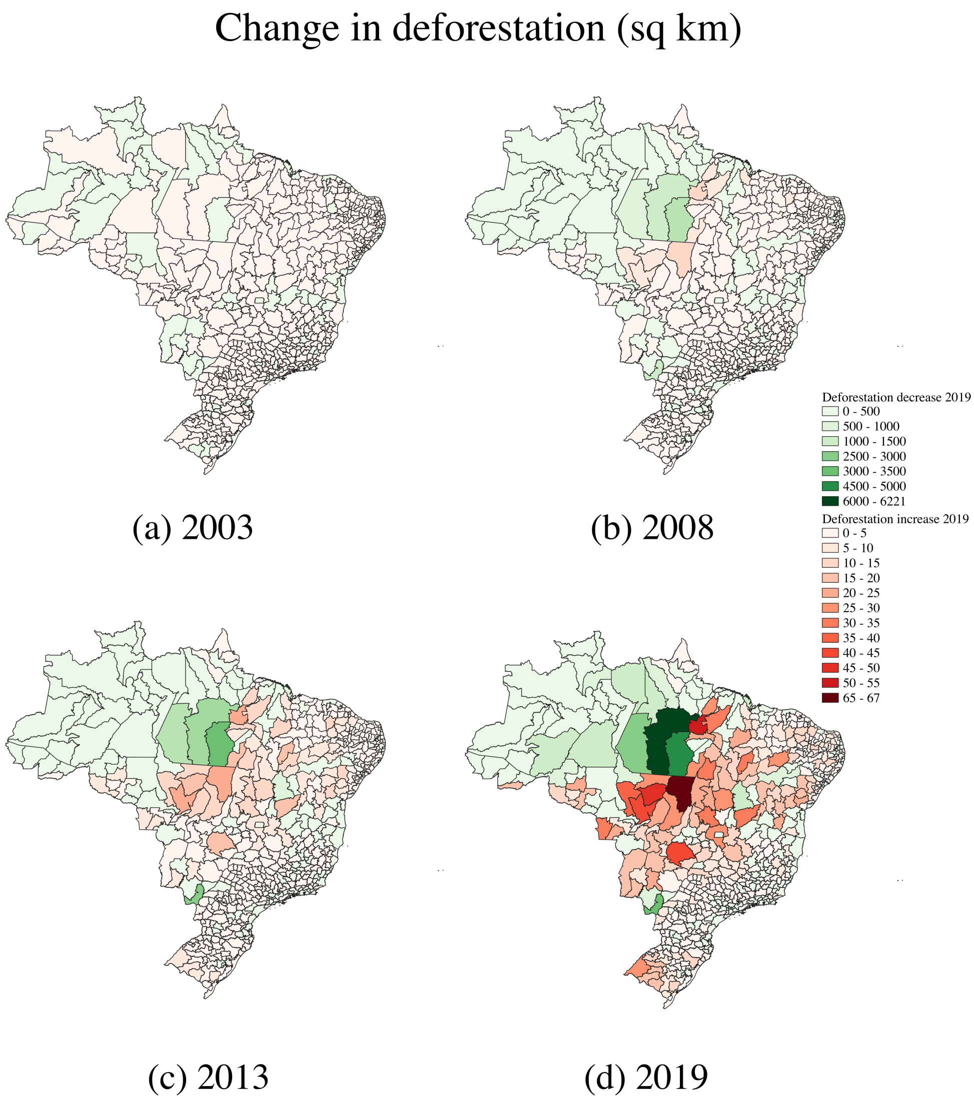
Protected Areas

Now let us look at the same results but for the Protected Areas. Figure 21 shows the trends in deforestation for the same three scenarios: Control: policy with GE effects (i.e., as in the observed data); Counterfactual A: no policy (i.e., no new Protected Areas established from 2003 in equilibrium); and Counterfactual B: policy, no leakage (i.e., with prices as if there were no new Protected Areas).

In the maps below, one can see the changes in the total (from 2003) area deforested as a result of the policy. Figure 22 shows the difference between the data and counterfactual A while figure 23 shows the difference between the data and counterfactual B, which isolates the price-effects of the policy.

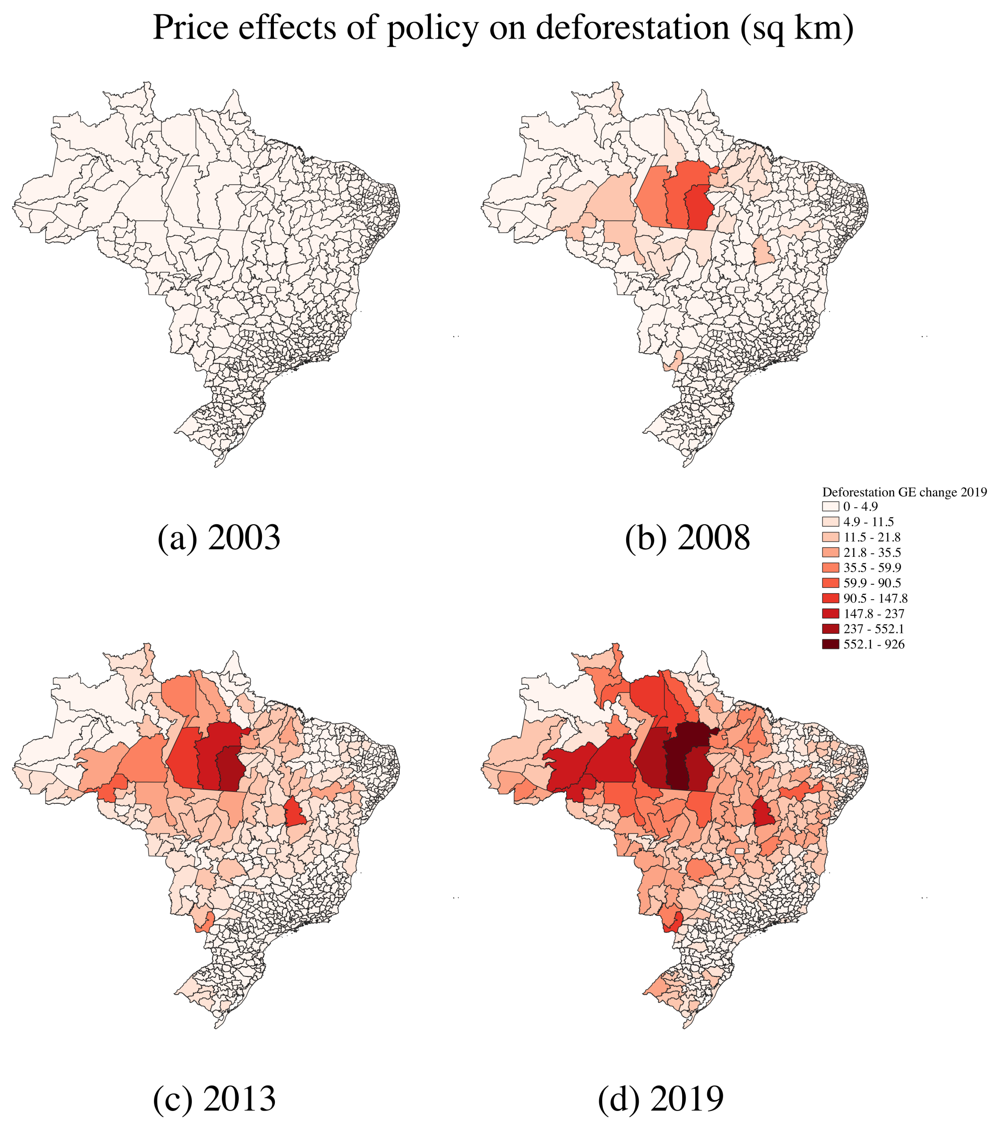
In this case, there is no meaningful distinction between GE effects in-situ and displacement. This is because we assume Protected Areas to lead to zero deforestation within them. There will be some leakage towards micro-regions with Protected Areas and some towards micro-regions without, but we do not consider this distinction meaningful as it depends arbitrarily on the way in which Protected Areas and micro-regions overlap. The graph below shows the percentage of leakage caused by Protected Areas. Interestingly, although the total

Figure 22: Counterfactual deforestation maps: Protected Areas



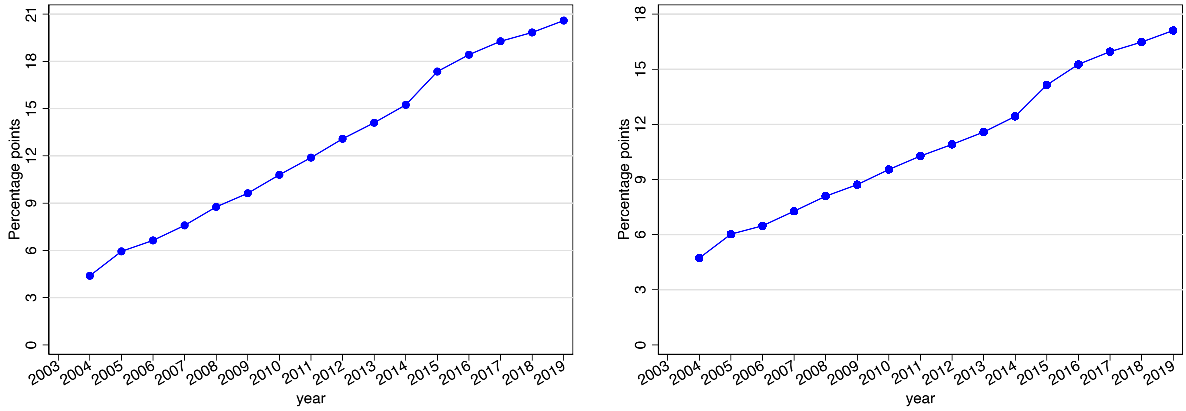
Note: This figure shows the new-Protected-Area-driven changes in cumulative deforestation (in thousands of squared kilometers) across the various microregions of Brazil for years 2003, 2008, 2013, and 2019. Specifically, it maps the differences between deforestation in the data (which includes the effect Protected Area policy) and the no-policy counterfactual simulation. The establishment of a Protected Area in part of a municipality leads to a direct reduction in deforestation by decreasing the area available for deforestation (T^F_{rt}), which mechanically reduces $Z^D_{rt} = \overline{Z}^D_{rt}(T^F_{rt})^{\psi}$. However, it also leads to an increase in deforestation via GE effects. Increases in deforestation seem to be of a much smaller magnitude overall.

Figure 23: General Equilibrium Effects maps: Protected Areas



Note: This figure shows the spatial distribution of the part of new-Protected-Area-driven changes in cumulative deforestation (in thousands of squared kilometers) that is due to GE effects. Namely, it is the difference between the scenario with new Protected Areas established (data) and the scenario with TFPs as in the data, but prices as in the no-new-Protected-Areas simulation. The spatial units are the various microregions of Brazil for years 2003, 2008, 2013, and 2019.

Figure 24: Cumulative leakage: Protected Areas



(a) Leakage of area deforested

(b) Leakage of Carbon emissions

Note: This figure shows the evolution of the leakage of the establishment of Protected Areas from 2003 until 2019. The blue line indicates the total percentage of (cumulative) avoided deforestation that is outdone by increases due to GE effects ("leakage"), following formula (20). Panel (a) shows leakage in terms of area deforested while panel (b) shows leakage in terms of carbon emissions. Carbon emissions are calculated using the micro-region level average of the carbon density (including both above- and below-ground) of natural ecosystems in 2010.

deforestation reduction caused by the new Protected Areas is lower than that of the Priority List, their leakage is higher. This is because they do not target the regions with the highest fundamental productivity of deforestation and hence they remain available to absorb the increased demand for land caused by Protected Areas.

Overall, the conclusion from the simulation exercise is that, even though there is a detectable amount of leakage to non-targeted areas in localised anti-deforestation policies, it does not mean that such policies are ineffective in reducing global deforestation. Both localised policies implemented by the Brazilian government over the past decades were, not only effective in reducing deforestation locally, but were able to retain at least 80% of this effect when considering national deforestation levels for the following 15 years. This finding suggests that concerns about leakage outdoing the majority of gains in localised anti-deforestation policies might be unwarranted, and that these policies may be effective in reducing global forest loss. Even more importantly, this exercise teaches us that targeting the areas with highest rates of deforestation is not only ideal to maximize deforestation reductions but also to minimize GE implications which may (i) undermine the goals of the policy, (ii) bias identification, and (iii) lead to economic losses.

7 Conclusion

To what extent do spatially targeted policies are globally effective when considering the possible geographical displacement of environmental damage as a response to the policy? The answer to this question has deep implications for policy design, given the global public good nature of ecosystem conservation. We address this issue in the context of tropical deforestation - an activity that has been responsible for one-fifth of global CO2 emissions in the past two decades - in Brazil - home to a third of the world's remaining rainforests.

The issue of conservation leakage is intrinsically a general equilibrium problem in space: a policy crackdown on deforestation in a spatially delimited region changes economic incentives through a shock to the price of deforested land, generating both sectoral and spatial reallocation. This reallocation depends on the costs of deforestation, the productivity of industries with varying land-intensity, consumers' substitution elasticities between goods and between origins, trade costs, regional amenities and migration frictions. Consequently, reduced-form evaluations conflate deforestation reduction in targeted areas with leakage to non-targeted ones. To separate these two effects, we develop a multi-sector spatial economic model of the Brazilian economy. Given the tight link between deforestation and agriculture, we model agricultural land as the endogenous output of a deforestation sector intermediate to the production of agricultural goods.

We apply our framework to quantify the global effects on national deforestation of two spatially targeted policies implemented by the Brazilian government over the past decades: the establishment of priority regions with high levels of illegal deforestation that receive extra resources for command and control, and the delimitation of protected areas with high forest coverage where deforestation is entirely banned. We find that both policies are highly effective in reducing global deforestation. Over a period of 12 years, leakage outside of targeted areas undoes between 10% and 15% of the policy impact in targeted areas.

Overall, we show that localised policies can be effective in reducing overall deforestation. Our theoretical framework provides a useful starting point to answer other questions of interest that require a spatial general equilibrium model of the relationship between deforestation and agricultural goods. Future research can build on our framework to study, for example, other indirect consequences of deforestation such as its impact on rainfall in nearby areas (Leite-Filho et al., 2021), or the role of technological change in agriculture on environmental conservation.

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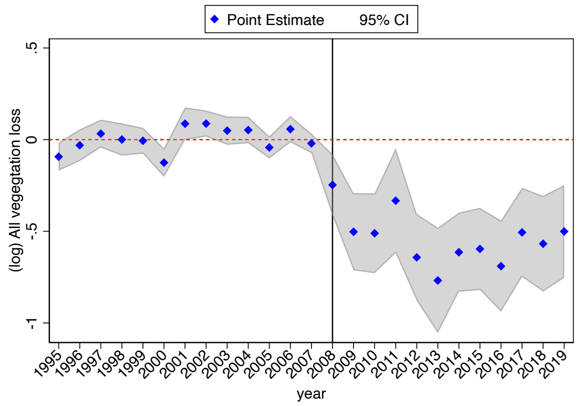
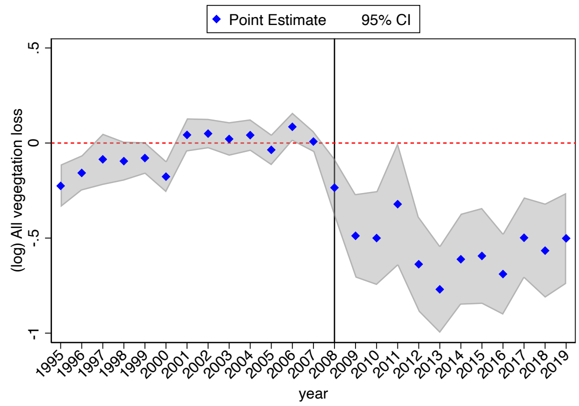
A Robustness of reduced-form analysis of Priority List and Protected Areas

As a robustness check, we do this analysis taking 10 km-wide hexagons as the unit of analysis. Municipalities that get selected to join the Priority List are different in a few fundamental ways: they are larger, closer to the forest frontier, and had different forest cover and deforestation trends than the rest of the Legal Amazon. The advantage of using the grid cell as opposed to the municipality as unit of analysis is that it allows us to better match the areas inside Priority Listed municipalities to areas outside. Having a much larger sample size of comparable units with the same area, we can more accurately reweight and match pre-policy trends.

Figure 25: Dynamic effects of Priority List on Forest Cover Changes (grid-level)



(a) (log) All loss of natural vegetation, no controls



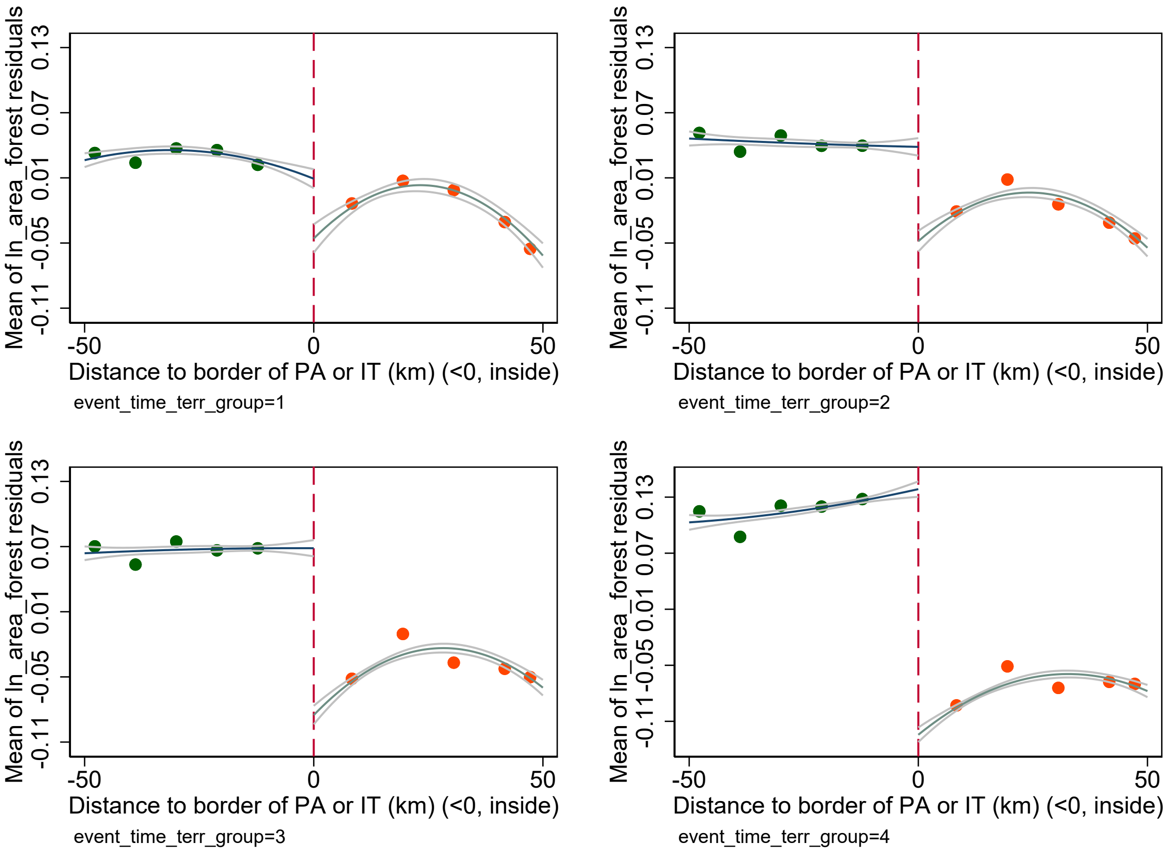
(b) (log) All loss of natural vegetation, with controls

Note: This figure shows the 10 km hexagon grid cell level event study of the synthetic differences in differences regression of agricultural area stocks (specifically: total agricultural area, cropland area, and pasture area) in logarithms on the onset of the Priority List in 2008. Since treatment is staggered, we restrict attention to the municipalities that join the Priority List in 2008 and those that never join as a pure control group. We only include hexagons in municipalities in the Brazilian Legal Amazon, as they are more likely to resemble Priority List municipalities. Standard errors are calculated via bootstrap with 50 repetitions.

Another advantage of considering grid-level outcomes is that we can control for two variables that might be confounding the estimation. The vast majority of deforestation happens near the forest edge. It could be that as the forest edge moves further North and West, places are simultaneously more likely to be deforested and to become part of the Priority List. Second, we control for whether a hexagon is part of a protected area, since the timing of protected area establishment and Priority Listing might be correlated. The left panel of 25 shows the dynamic results of a synthetic diff-in-diff analysis on the total natural forest loss without controls.[30] The right panel adds controls for: (i) the log of the absolute value of the distance to the forest edge, (ii) a dummy for being in an indigenous territory, (iii) a dummy for being inside a protected area. Reassuringly, the grid-level results are very similar in significance and magnitude to the municipality-level analysis. The only difference is that the grid-level analysis shows better matched pre-trends and does not show a reversal in the deforestation reduction.

[30]To speed up the analysis we do it on a 10% random sample of all the hexagons in the Legal Amazon.

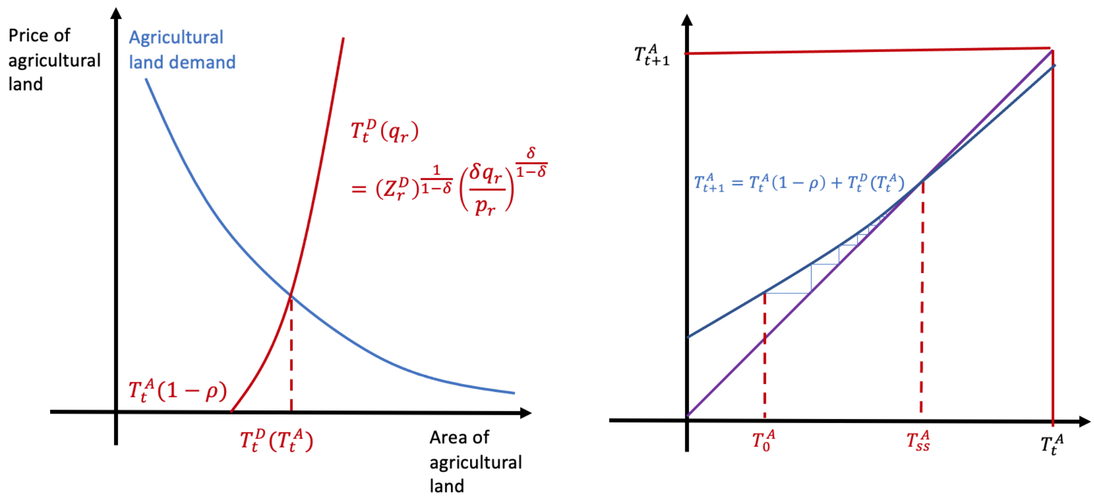
Figure 26: Discontinuities in forested area around borders of Protected Areas, by: period relative to the introduction of conservation policy



Note: This figure illustrates the discontinuity in forested area around the borders of protected areas, before and after they are protected. More specifically: the top-left panel considers 10+ years before the protection of the nearest area, the top-right 0-10 years before, the bottom-left 0-10 years after, and the bottom-right 10+ years after. Each dot represents the mean log-forested area within bins of 10 km around the border of all protected areas, from 50km inside of 50km outside. The x-axis shows distance to the border, with negative (positive) values indicating the area inside (outside) the protected area. Here the hexagons are classified according to the minimum (and final, since it can only decrease) distance they ever have from a Protected Area across all periods in the sample, but their forest area is only considered for years in which (i) they area 10+ years from reaching that minimum distance, (ii) they are 0-10 years away from reaching that minimum distance, (iii) they reached it 0-10 years ago, (iv) they reached it 10+ years ago.

B Agricultural Land Accumulation with Forest Regrowth

Figure 27: Agricultural Land Accumulation with Forest Regrowth



Note: This figure illustrates the transition dynamics in the market for agricultural land under a constant forest regrowth rate. The graph on the left shows supply and demand curves for land, and the equation for the equilibrium in the market for the equilibrium quantity. The graph on the right shows the transition curve for agricultural land: with forest regrowth, deforestation reaches a steady state, where the blue curve intercepts the 45-degree line.

"

B.1 Deriving local expenditure by sector

Wages in equilibrium assuming Frechet Frank-copula. Let the joint distribution of pairs of individual productivities (z_{ir}^A, z_{ir}^{NA}) is given by the Frank copula as in LW with parameters $(\chi^A, \chi^{NA}, \rho)$. Then there are no simple closed-form expressions for the share of employment in agriculture and the labour income in each sector. Instead,

$$s_r^A = Pr\left[z_{ir}^{NA}/z_{ir}^A \leq w_r^A/w_r^{NA_r}\right] = \int_0^\infty \int_0^{z^A w_r^A/w_r^{NA}} f(z^A, z^{NA})\, dz^{NA} dz^A$$

$$\overline{y}_r^{LA} = w_r^A \mathbb{E}\left[z_{ir}^A \middle| z_{ir}^{NA}/z_{ir}^A \leq w_r^A/w_r^{NA_r}\right] = w_r^A \frac{1}{s_r^A} \int_0^\infty \int_0^{z^A w_r^A/w_r^{NA}} z^A f(z^A, z^{NA})\, dz^{NA} dz^A$$

$$\overline{y}_r^{LNA} = w_r^{NA} \mathbb{E}\left[z_{ir}^{NA} \middle| z_{ir}^{NA}/z_{ir}^A > w_r^A/w_r^{NA_r}\right] = w_r^{NA} \frac{1}{s_r^{NA}} \int_0^\infty \int_{z^A w_r^A/w_r^{NA}}^\infty z^{NA} f(z^{NA}, z^{NA})\, dz^{NA} dz^A$$

C Model inversion

Given all production and preference parameters, the distribution of population, initial land endowments, and K+3 vectors of observable endogenous quantities

$$\{s_r^A, T_r^D, p^{NAr}Y_r^{NA}, \{T_r^{Ak}, p^{Akr}Y_r^{Ak}\}_k\}_r,$$

below I formulate the system of equations that need to be solved in order to find the regional TFPs and amenities.

The Cobb-Douglas form of agricultural income of a each commodity k in region r yields

$$p^{Akr}Y_r^{Ak} = \frac{v_r T_r^{Ak}}{\alpha_k} \tag{21}$$

Adding up over all k,

$$v_r = \frac{1}{T_r^A}\sum_k \alpha_k p^{Akr}Y_r^{Ak}. \tag{22}$$

GDP accounting

$$\sum_k p^{Akr}Y_r^{Ak} + p_r^{NA}Y_r^{NA} = L_r \overline{y}_r^L + v_r T_r^A \tag{23}$$

so

$$\overline{y}_r^L = \frac{1}{L_r}\Big(\sum_k p^{Akr}Y_r^{Ak} + p_r^{NA}Y_r^{NA} - v_r T_r^A\Big) \tag{24}$$

Having the regional prices at origin (start with a guess), we can get goods prices at destination

$$p_d^s = \Big(\sum_{r=1}^{R}(\tau_d^r p^{sr})^{1-\sigma}\Big)^{\frac{1}{1-\sigma}} \tag{25}$$

$$p_r^A = \Big(\sum_{k=1}^{K}(p^{Akr})^{1-\theta}\Big)^{\frac{1}{1-\theta}} \tag{26}$$

$$p_r = (p_r^A)^{\phi}(p_r^{NA})^{1-\phi} \tag{27}$$

Land prices

$$q_r = \frac{1}{1-\beta(1-\rho)}v_r \tag{28}$$

Deforestation investment

$$p_r I_r^D = \delta q_r T_r^D \tag{29}$$

Local household expenditure

$$E_r = v_r T_r^A + \overline{y}_r^L L_r - p_r I_r^D \tag{30}$$

Local expenditure shares in agriculture

$$\vartheta_r^A = \phi + \nu \left(\frac{p_r^A}{p_r^{NA}} \right) \left(\frac{E_r}{p_r L_r} \right)^{-\eta} \lambda_r \tag{31}$$

where $\lambda_r \equiv \frac{\mathbb{E}\left((y_{ir})^{1-\eta}\right)}{\left(\mathbb{E}(y_{ir})\right)^{1-\eta}}$ Regional expenditures in each sector

$$X_d^A \equiv \vartheta_d^A E_d + \phi p_d I_d^D, \quad X_d^{NA} \equiv (1 - \vartheta_d^A) E_d + (1 - \phi) p_d I_d^D$$

$$X_d^{Ak} = X_d^A \left(\frac{p_d^{Ak}}{p_d^A} \right)^{1-\theta}$$

Rewrite trade shares as

$$\pi_d^{so} = (\tau_d^o p^{so})^{1-\sigma} (p_d^s)^{\sigma-1}$$

in order to solve for updated origin prices (for contraction mapping) in the market clearing equations

$$T_r^{Ak} v_r = \sum_{d=1}^{R} \alpha_k (\tau_d^r p^{Akr})^{1-\sigma} (p_d^{Ak})^{\sigma-1} X_d^{Ak} \tag{32}$$

$$= (p^{Akr})^{1-\sigma} \sum_{d=1}^{R} \alpha_k (\tau_d^r)^{1-\sigma} (p_d^{Ak})^{\sigma-1} X_d^{Ak}. \tag{33}$$

Solving for p^{Akr},

$$p^{Akr} = \left(\frac{T_r^{Ak} v_r}{\alpha_k} \right)^{\frac{1}{1-\sigma}} \left(\sum_{d=1}^{R} (\tau_d^r)^{1-\sigma} (p_d^{Ak})^{\sigma-1} X_d^{Ak} \right)^{\frac{1}{\sigma-1}}. \tag{34}$$

Similarly, for the non-agricultural sector,

$$p^{NAr} = \left(\overline{y}_r^L (1 - s_r^A) L_r \right)^{\frac{1}{1-\sigma}} \left(\sum_{d=1}^{R} (\tau_d^r)^{1-\sigma} (p_d^{NA})^{\sigma-1} X_d^{NA} \right)^{\frac{1}{\sigma-1}}. \tag{35}$$

To back out the Z_r^s, first solve for w_r^A and w_r^{NA},

$$w_r^A = \lambda^{-1}\overline{y}_r^L(s_r^A)^{1/\chi}, \quad w_r^{NA} = \lambda^{-1}\overline{y}_r^L(1-s_r^A)^{1/\chi} \tag{36}$$

Then

$$Z_r^{Ak} = \frac{1}{p_r^{Ak}}\Big(\frac{w_r^A}{1-\alpha_k}\Big)^{1-\alpha_k}\Big(\frac{v_r^A}{\alpha_k}\Big)^{\alpha_k} \tag{37}$$

$$Z_r^{NA} = \frac{1}{p_r^{NA}}w_r^{NA} \tag{38}$$

Aggregate market clearing. Because of market clearing and the fact that the trade shares from all origins add up to 1 for each destination, it follows that

$$\sum_{r=1}^{R} L_r(1-s_r^A)y_r^{LNA} = \sum_{r=1}^{R}\sum_{d=1}^{R}\pi_d^{NAr}X_d^{NA} = \sum_{d=1}^{R}X_d^{NA} \tag{39}$$

$$= \sum_{d=1}^{R}\Big[(1-\phi)p_dY_d - \nu E_d^{1-\eta}\Big(\frac{p_d^A}{p_d^{NA}}\Big)(p_dL_d)^{\eta}\frac{\mathbb{E}\big((y_{id})^{1-\eta}\big)}{\big(\mathbb{E}(y_{id})\big)^{1-\eta}}\Big] \tag{40}$$

And if we decompose region-sector consumer price indices p_d^s as the product of a Brazil-wide sectoral price index $p^s \equiv \Big(\sum_{o=1}^{R}(p^{so})^{1-\sigma}\Big)^{\frac{1}{1-\sigma}}$ and a region specific component $\tilde{p}_d^s \equiv p_d^s/p^s$, then we can solve for a Brazil-wide relative price index of agriculture:

$$\frac{p^A}{p^{NA}} = \Bigg(\Big[\sum_{d=1}^{R}(1-\phi)p_dY_d - \sum_{r=1}^{R}L_r(1-s_r^A)y_r^{LNA}\Big]\Big/\Big[\sum_{d=1}^{R}\nu E_d^{1-\eta}\Big(\frac{\tilde{p}_d^A}{\tilde{p}_d^{NA}}\Big)(p_dL_d)^{\eta}\frac{\mathbb{E}\big((y_{id})^{1-\eta}\big)}{\big(\mathbb{E}(y_{id})\big)^{1-\eta}}\Big]\Bigg) \tag{41}$$

Aggregate agricultural expenditure share in each region The share of consumer expenditure in agriculture of a household with expenditure e_i equals

$$\vartheta_{ir}^A = \phi + \nu\Big(\frac{p_r^A}{p_r^{NA}}\Big)\Big(e_{ir}\Big)^{-\eta}p_r^{\eta}. \tag{42}$$

Thus, the total agricultural expenditure in region r equals

$$X_r^A = \phi p_r I_r^D + \int \vartheta_{ir}^A e_{ir}\,dG(i) = \phi(E_r + p_rI_r^D) + \nu\Big(\frac{p_r^A}{p_r^{NA}}\Big)p_r^{\eta}\int \Big(e_{ir}\Big)^{1-\eta}dG(i),$$

Assume that people with higher labour incomes get proportionately higher land rents and also spend proportionately more on deforestation. Define the ratio between land rents and labour income from the aggregates, a_r, and the ratio of the total income spent on deforestation investments, b_r.

$$a_r \equiv \frac{v_r T_r^A}{\int_i y_{ir}^L dG(i)}, \quad b_r \equiv \frac{p_r I_r^D}{\int_i y_{ir}^L dG(i) + v_r T_r^A}.$$

Then the assumption of proportional land rents and deforestation expenditures can be expressed formally as:

$$(1)\, y_{ir}^T = a_r y_{ir}^L, \quad (2)\, x_{ir}^d = b_r y_{ir} \implies (3)\, \frac{e_{ir}}{y_{ir}^L} = (1+a_r)(1-b_r) \equiv m_r$$

$$e_{ir} = \underbrace{\max\{w_r^{NA} z_{ir}^{NA}, w_r^A z_{ir}^A\}}_{y_{ir}^L} m_r,$$

where

$$m_r = \frac{E_r}{L_r \overline{y}_r^L}, \quad \overline{y}_r^L = s_r^A y_r^{LA} + s_r^{NA} y_r^{LNA} = \mathbb{E}(y_{ir}^L)$$

For the second term of the total agricultural expenditure equation, we compute the following integral

$$\begin{aligned}
\int (e_{ir})^{1-\eta} dG(i) =& (m_r)^{1-\eta} L_r \mathbb{E}\big((y_{ir}^L)^{1-\eta}\big) \\
\mathbb{E}\big((y_{ir}^L)^{1-\eta}\big) =& \Bigg(\int_0^\infty \int_0^{z^A w_r^A / w_r^{NA}} (w_r^A z^A)^{1-\eta} f(z^A, z^{NA})\, dz^{NA} dz^A \\
& + \int_0^\infty \int_{z^A w_r^A / w_r^{NA}}^\infty (w_r^{NA} z^{NA})^{1-\eta} f(z^A, z^{NA})\, dz^{NA} dz^A \Bigg)
\end{aligned}$$

Thus, the aggregate local share of consumer expenditure in agriculture equals

$$\vartheta_r^A = \phi + \nu \Big(\frac{p_r^A}{p_r^{NA}}\Big) \Big(\frac{E_r}{p_r L_r}\Big)^{-\eta} \frac{\mathbb{E}\big((y_{ir})^{1-\eta}\big)}{\big(\mathbb{E}(y_{ir})\big)^{1-\eta}}. \tag{43}$$

D Calibration of other parameters

D.1 Production Parameters

To estimate α_k for each agricultural commodity k, we rely on the 2006 Agricultural Census, a census of the universe of farming establishments. Using data on land prices, land in each agricultural activity, labour in each agricultural activity, and agricultural wages, we estimate how the ration of land income over rental income varies between pastures for cattle grazing, temporary crops, and perennials.

Let the area planted in each type of agricultural activity T_r^{Ak}, workers in type of agricultural activity N_r^{Ak}, labour incomes per capita in agriculture $\overline{y}_r^{LA}$, and land value q_r.

The Cobb-Douglas functional form of the agricultural production function and the zero-profit condition together imply that

$$\frac{\alpha_k}{1-\alpha_k} = \frac{\sum_{r=1}^{R} v_r T_r^{Ak}}{\sum_{r=1}^{R} \overline{y}_r^{LA} N_r^{Ak}}.$$

Doing this we find that the land share for pastures, temporary crops, and perennials vary significantly and they are, respectively: 0.71, 0.54, and 0.36. These differences make it so that there is greater substitutability between land and labour in agricultural production as a whole. This has important implications for leakage. Consider a region where the supply of agricultural workers increases. This could be due to more migration from regions where conservation policies have been enacted. Higher supply of agricultural workers increases the demand for agricultural land. In a model with multiple agricultural sectors, however, it might also shift land use away from very land intensive activities, for example cattle ranching, towards more labour intensive ones, such as perennial crops. The extent to which this happens in equilibrium would depend mainly on consumers willingness to substitute consumption between goods and on the slope of the supply of deforestation. If deforestation is very cheap and consumers very reluctant to substitute towards less land-intensive goods, cattle-ranching will remain preferable and the inflow of workers will lead to much deforestation. By contrast, in a region where deforestation is very costly and consumers readily substitute beef with soy, the increased supply of labour will mean farmers may opt to convert pastures to soy fields and demand very little deforestation.

D.2 Preference parameters

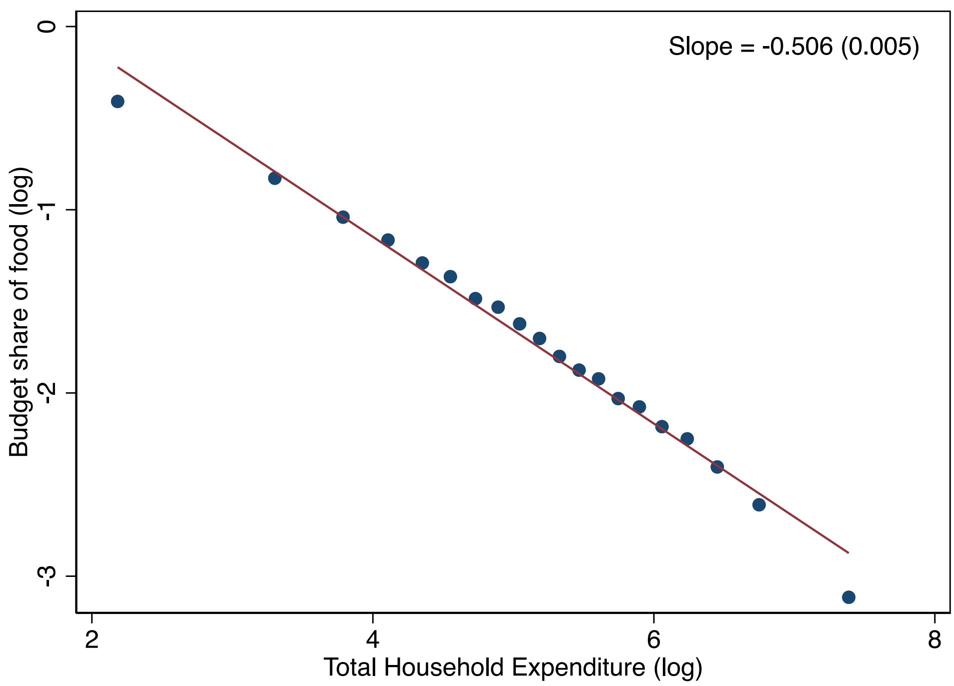
For PIGL parameters ϕ and ν, we take the values estimated by Eckert and Peters (2022). The parameter governing the non-homotheticity of preferences, η, also referred to as Engel elasticity, captures the rate at which higher-income consumers shift their budget shares away from agricultural goods (i.e. food items). We estimated by regressing the logarithm of the share of expenditure in food on the logarithm of total expenditure using the household-level data from the 2017/2018 consumer expenditure survey (POF). The table below shows the coefficients from that regression. For robustness, we consider both food expenditure as a share of total non-durables expenditure (column 1 - the preferred specification) and as a share of total household income (column 2).

Table 9: Estimation of η

	Outcome: log-budget share on food items	
	(1)	(2)
Log(Non-durable Expenditure)	-0.506***	
	[0.005]	
Log(Income)		-0.575***
		[0.008]
Constant	0.914***	0.632***
	[0.025]	[0.056]
R^2	0.309	0.195
Dep. Var. Mean	-1.730	-3.229
Observations	45322	45322

Note: This table displays the estimated Engel curve for food: the relationship between income and budget share of food, which illustrates the non-homotheticity in consumer preferences. The dots represent the average share of total household expenditure dedicated to food items for 20 bins of total household expenditure. Standard errors in parenthesis. *p<0.1, **p<0.05, *** p<0.01.

Figure 28: Engel curve for food consumption



Note: This figure displays the estimated Engel curve for food: the relationship between income and budghet share of food, which illustrates the non-homotheticity in consumer preferences. The dots represent the average share of total household expenditure dedicated to food items for 20 bins of total household expenditure.

D.3 Migration parameters

Recall that the utility of a migrant moving from origin o to destination d depends on: (i) consumption utility V_d, (ii) residential amenities B_d, (iii) an origin-destination migration cost μ_{od}, and (iv) an idiosyncratic preference shock with a Frechet distribution with shape parameter ϵ. These shocks are drawn every year when making migration decisions so that each year, the share of migrants from o that pick d as destination equals

$$\text{Share of Migrants}_d^o = \frac{\left(V_d B_d \mu_d^o\right)^{\epsilon}}{\sum_j \left(V_j B_j \mu_j^o\right)^{\epsilon}}.$$

The above is referred to as the migration gravity equation. To estimate it, first we take logs so that it becomes the following equation with origin and destination fixed effects

$$\log(\text{Share of Migrants}_d^o) = \delta_o + \delta_d + \epsilon \log\left(\mu_d^o\right). \tag{44}$$

Using bilateral migration flows between the 558 micro-regions according to the 2010 census, we use the equation above to estimate $\epsilon\mu_d^o$ and the correlation of (log) income and destination fixed effects to estimate ϵ. The preferred approach will be to estimate the full matrix of origin and destination bilateral migration utilities μ_d^o from the residuals of the regression of (log) migration rates of origin and destination fixed effects. Alternatively, we could estimate μ_d^o to be a function of the linear distance between micro-regions, $\mu_d^o = (\text{dist}_d^o + 1)^{\upsilon}$ from a regression of migration shares on log of distance plus 1 with origin and destination fixed effects as reported in table 10, column (1). We add one so that $\mu_o^o = 1$ and $\mu_d^o(\text{dist}_d^o)$ is a decreasing function of distance as long as $\upsilon < 0$. The distance elasticity of migration is estimated to be -1.55.

To estimate ϵ, note that the destination fixed effect, according to the structure of the model, depends on income at destination and amenities as follows,

$$\delta_d = \epsilon \log(V_d) + \epsilon \log(B_d). \tag{45}$$

And $\log(V_d)$, up to an approximation of equation 7, is $\log(V_d) \approx \eta \log(e_d/p_d) - \log(\eta)$. Thus, following Buggle et al. (2023), we estimate ϵ from a regression of the fixed effect on the estimated fixed effects on the logarithm of income in the 2010 census. The income used in this regression is the income of those people who were in-migrants to destination d. Although average income and real expenditure (e) are not the same thing, as long as they are proportional, a regression of destination fixed effects on income can help us estimate ϵ. Column (2) below show results of PPML regression, where we get $\epsilon\eta = 0.633$, which

Table 10: Estimation of migration parameters

	(1) Share of Migrants	(2) Destination F.E.	(3) Destination F.E.
log(Distance+1)	-1.550***		
	[0.002]		
log(Mig. income)		0.633***	
		[0.044]	
log(Avg. income)			0.646***
			[0.043]
Origin FE	Yes	No	No
Dest. FE	Yes	No	No
Pseudo R2	0.805	0.25	0.27
Observations	3.11e+05	558	558
Method	PPML	PPML	PPML

Note: This table displays the results of the regressions used for the estimation of migration parameters. Column (1) is a Poisson Pseudo Maximum Likelihood (PPML) regression of bilateral migration shares in the past 5 years at the micro-region level on the log of their distance plus 1. Migration data comes from the 2010 population census. The regression includes origin and destination fixed effects Column (2) is also a PPML regression. It has as dependent variable the destination fixed effect estimated from a PPML as in column (1) but without the fixed effects only, and not the log of distance plus 1, as specified in (44). The coefficient displayed is the coefficient on the log of the average income of migrants according to the 2010 population census. Column (3) is as column (2) but considers the average income of all people living in the destination micro-region. Standard errors in parenthesis. *p<0.1, **p<0.05, *** p<0.01.

implies $\epsilon = 1.25$ for the estimated $\eta = 0.506$. Two concerns with this method are (i) endogeneity: income may be correlated with amenities, which would bias the estimation and (ii) measurement error: we use income instead of expenditure and we do not divide incomes by their regional price index, which is unobserved. A potential solution to be implemented include using a panel of migration flows from older and newer census data, and including micro-region and year fixed effects, as in Buggle et al. (2023).

D.4 Trade parameters

Iceberg trade costs are estimated to fit trade costs in 1999 and 2017 from the residuals in the regression equation of (log) trade flows with origin and destination fixed effects. Taking logarithms from equation 8, and sending the volume of expenditure of consumers in region d to the right hand side so that the data on trade flow rather than shares can be used, yields

$$\log X_d^o = \log p^o - \log p_d X_d + (1-\sigma)\log(\tau_d^o)$$

Notice that these data do not include the observations for which the origin and the destination are the same, as it is data from inter-state customs. Thus, if we assume that $\tau_d^o = (\text{dist}_{od}+1)^{\kappa}$, then the coefficient of the log-log regression of trade flows on distance (+1) with origin and destination fixed effects equals $\kappa(1-\sigma)$. Given the results from the regressions reported in the table below, $\kappa \approx \frac{-0.9}{1-9} \approx 0.11$.

Table 11: Estimation of trade parameters

	Outcome: log-trade flows	
	(1)	(2)
log(Distance+1)	-0.871***	-0.916***
	[0.053]	[0.036]
Year	1999	2017
Origin FE	Yes	Yes
Dest. FE	Yes	Yes
Pseudo R2	0.966	0.957
Observations	702	702

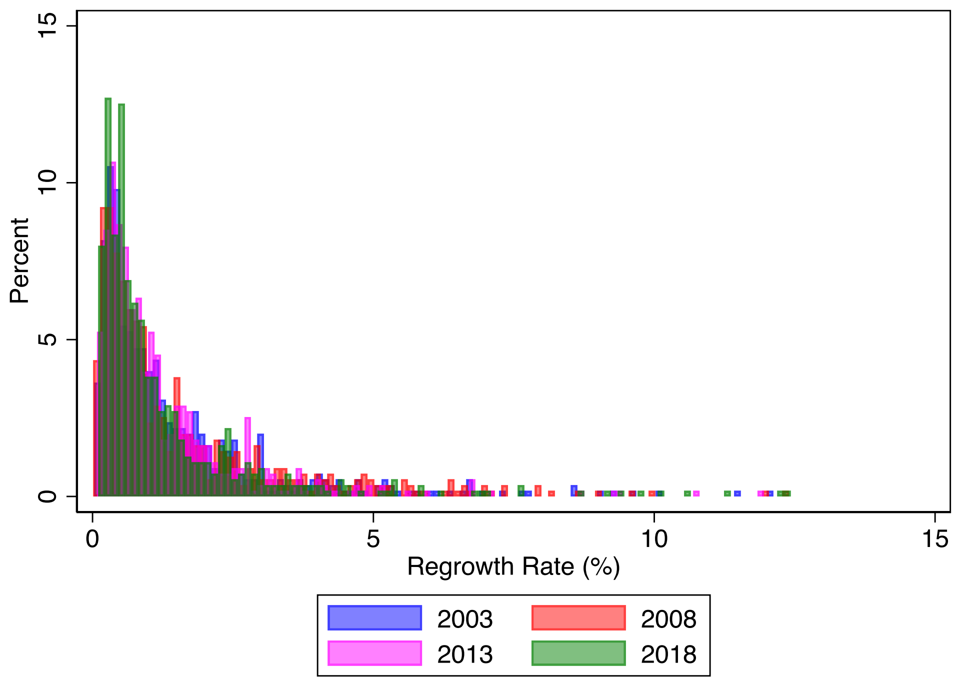
Note: This table displays the results of the regressions used for the estimation of trade parameter κ that governs the distance-elasticity of trade. They are OLS regressions of the bilateral trade flows between different states on the log of their distance plus with origin and destination fixed effects. The structural interpretation of the coefficient is that it equals $(1-\sigma)\kappa$. Column (1) uses 1999 state-level trade flow data and column (2) uses 2017 trade flow data. Standard errors in parenthesis. *p<0.1, **p<0.05, *** p<0.01.

D.5 Regrowth rate

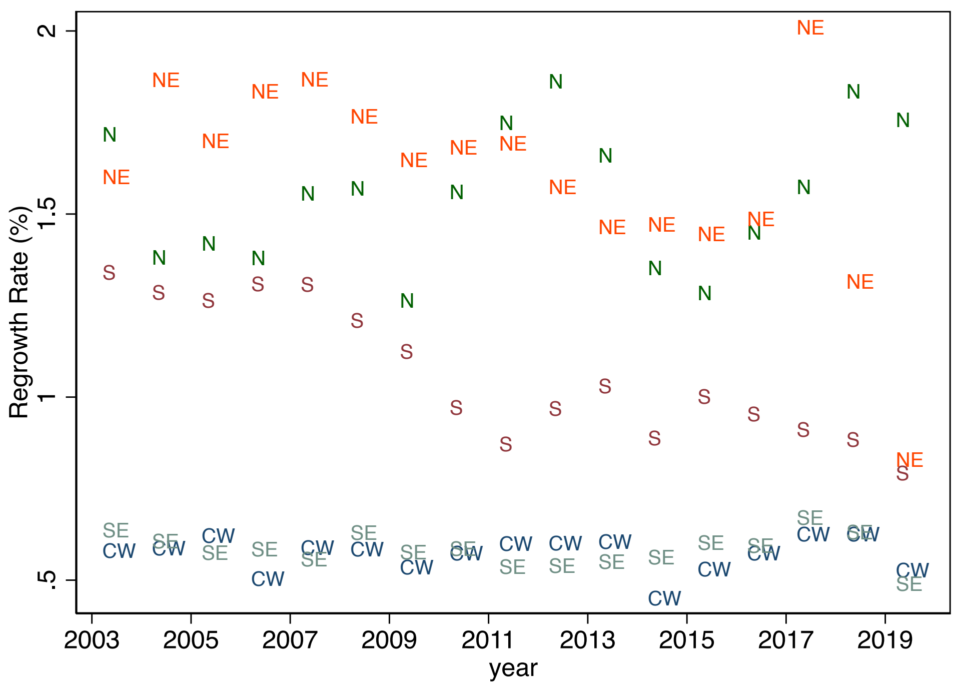
The distribution of regrowth rates is shown in Figure 29, panel (a) for four different years in the model period. We can see that the mode of the regrowth rate distribution is around 0.3%, and there is a long right tail, with the 99th percentile having 13% and the largest regrowth rate being 60%. For simplicity, we abstract away from this heterogeneity and take one regrowth rate for all of Brazil. To inform where this heterogeneity comes from and the extent to which regrowth rates are changing over time, in panel (b) we plot the regrowth rates by Brazil's large regions: North (N), North-East (NE), South (S), Center-West (CW), and South-East (SE).

D.6 Model fit

Figure 29: Forest regrowth rates



(a) Distribution of forest regrowth rates of microregions



(b) Trends of forest regrowth rates by 5 regions

Note: The figures above illustrate the regional and temporal variation of forest regrowth rates across Brazil. Forest regrowth is defined as the percentage of non-forest area that becomes forest in a given year. Panel (a) above shows the distribution of regrowth rates by micro-region for 4 different years: 2003, 2008, 2013, and 2018. Panel (b) shows the yearly regrowth rates of Brazil's five large macro-regions: the North East (NE), the North (N), the South (S), and the Centre-West (CW) for every year in the study period of the counterfactual analysis (2003-2020).

Figure 30: Model fit: land prices

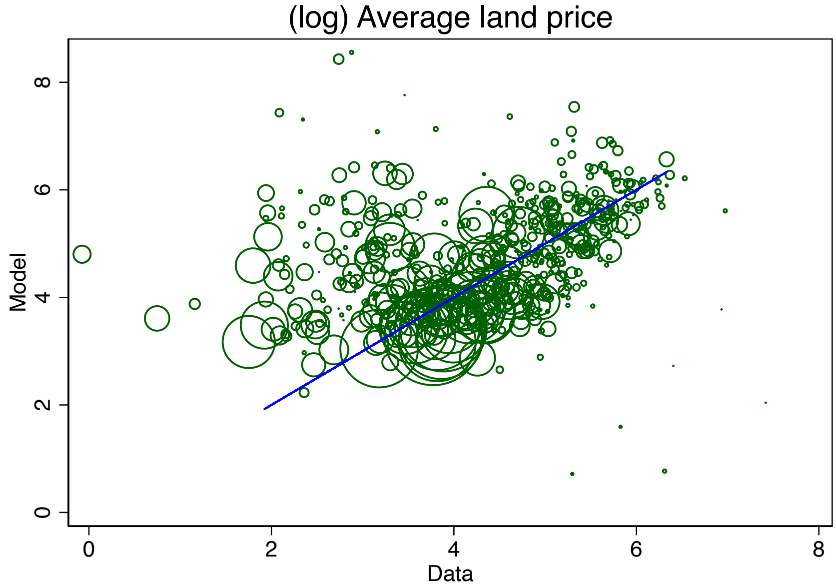
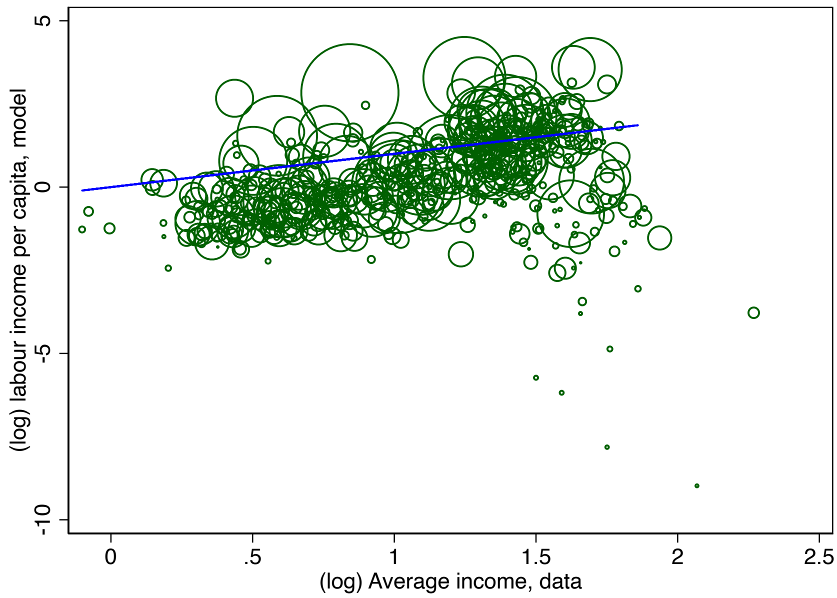


Figure 31: Model fit: comparing predicted and observed land prices

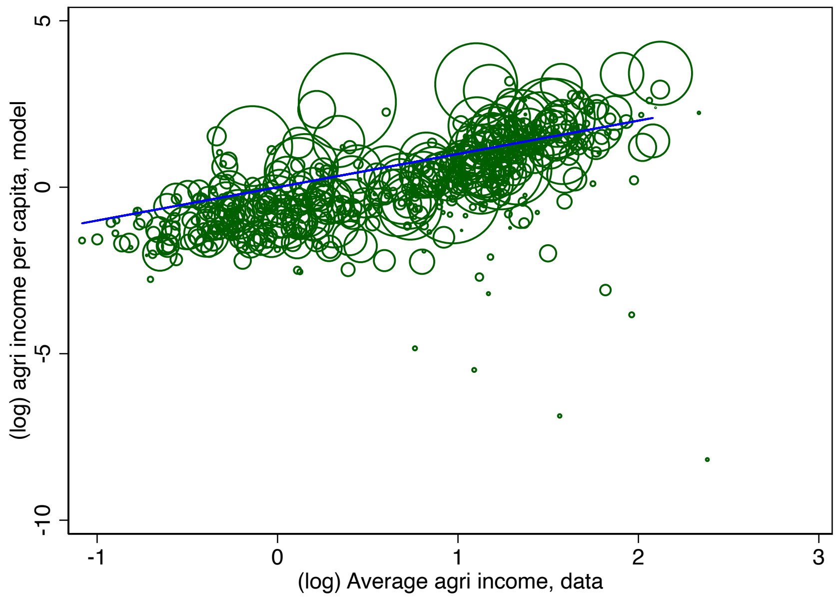
Note: This compares the predicted land prices from model calibration q_r with observed land value. Each circle is a micro-region, and the size of the circle corresponds to the total agricultural area

Figure 32: Model fit: labour income



Note: This compares the predicted average labour income from model calibration y_r^L with observed average labour income. Each circle is a micro-region, and the size of the circle corresponds to the total agricultural area

Figure 33: Model fit: labour income in agriculture



Note: This compares the predicted average labour income from model calibration y_r^{LA} with observed average labour income from the agricultural sector. Each circle is a micro-region, and the size of the circle corresponds to the total agricultural area

Figure 34: Model fit: value added in agriculture

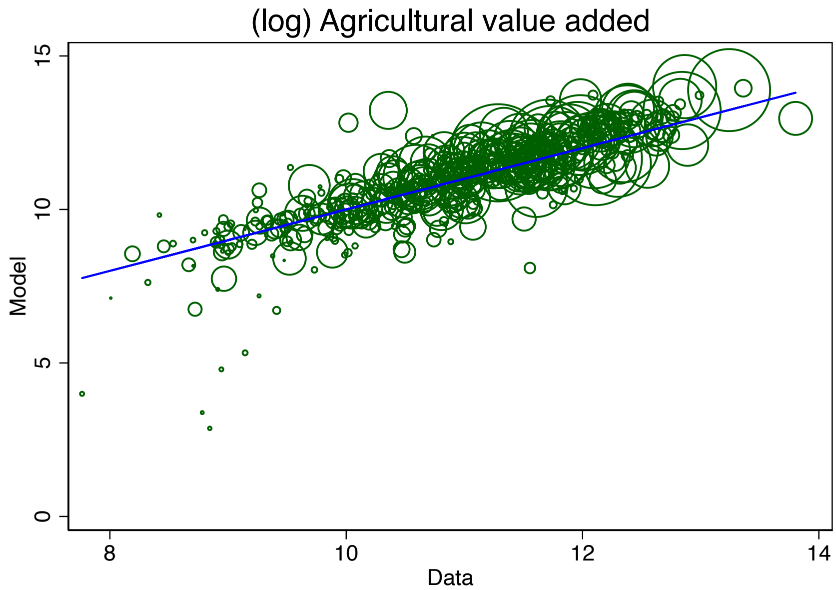
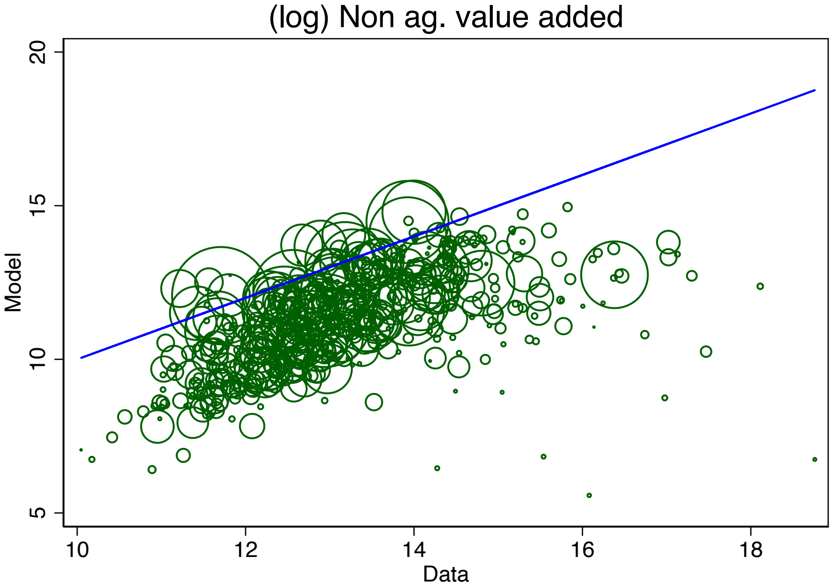


Figure 35: Model fit: comparing predicted and observed agricultural value added

Note: This compares the predicted total GDP in the agricultural sector from model calibration with observed value added from the agricultural sector. Each circle is a micro-region, and the size of the circle corresponds to the total GDP

Figure 36: Model fit: value added in non-agriculture



Note: This compares the predicted total GDP in the non-agricultural sector from model calibration with observed value added from the non-agricultural sector. Each circle is a micro-region, and the size of the circle corresponds to the total GDP