# Technological Progress and Climate Change: Evidence from the Agricultural Sector

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**Abstract**

We provide evidence of how technological progress affects greenhouse gas emissions. Using a dynamic difference-in-differences design, we show that producers in Brazilian localities with high suitability for genetically engineered seeds increase crop output by substituting away from higher-emission activities (such as livestock breeding). This increase in crop output is not accompanied by deforestation and fires—two major greenhouse gas emitters. Further, our findings indicate that the agriculture sector emits greenhouse gases more efficiently after the land-use change, generating more output for a given emission level. Our evidence suggests that technological innovations may increase production and simultaneously offset emissions.

***Keywords:*** *Climate change, Greenhouse gas emissions, Environment, Agricultural technology, Genetically engineered seeds.*

***JEL Classification:*** *Q50, Q02, O13, O33.*

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# 1 Introduction

Understanding the implications of technological progress to the environment lies at the heart of contemporary policy debates. Throughout history, leaps in technological progress commonly led to environmental damages—the most prominent historical example arguably being the Industrial Revolution. More recently, rising concerns about climate change have ignited debates on reducing greenhouse gas (GHG) emissions and avoiding further environmental degradation. However, systematic evidence on how productivity-enhancing innovations affect GHG emissions—a global externality and the primary cause of climate change (IPCC, 2021)—is scarce. Evidence of this most pressing issue is essential to understand how technology can help reduce emissions and how policy can counteract environmental costs related to technological progress.

The food production sector is a suitable setting for studying the trade-off between environmental preservation and economic growth. Guaranteeing food security in a scenario of crescent demand for food is a recurring topic dating back to at least Malthus; the expected rise in the world's food demand is likely to place further pressure on GHG emissions in the coming decades. Furthermore, growing evidence suggests that the agricultural sector can be considered both a “victim" and a “culprit" of climate change. Extreme climate conditions can severely compromise agriculture by shifting rainfall regimes or turning productive areas into deserts (Burrell, Evans, & De Kauwe, 2020; Conte, Desmet, Nagy, & Rossi-Hansberg, 2020). By contrast, food production accounts for approximately one-third of worldwide emissions (Poore & Nemecek, 2018).

Can technological advances mitigate climate change by offsetting GHG emissions? We examine this question in the context of the Brazilian agricultural sector. Brazil is a key player on the world stage: the country is one of the largest agricultural producers and a leading exporter of several commodities (FAOSTAT, 2020). In addition, data show that more than half of Brazil's GHG emissions stem from deforestation and agriculture-related activities (Da Mata & Dotta, 2022). Therefore, agricultural production responses to shocks in our setting can result in significant global externalities.

To study the impacts of technology on emissions, we explore the introduction of genetically engineered soybean seeds (henceforth, GE soybean seeds or GE soy/seeds) in Brazil. We examine how producers re-optimize their production choices after adopting GE seeds and how these choices affect emissions. At least three features of GE seeds are crucial to this study. First, the herbicide-resistant GE seeds increase productivity (output per area). As a result, this significant increase in agricultural productivity allows places to expand their production frontier and change factor intensity—including the demand for land. The changing land demand means that GE seeds may cause land-use change (e.g., substituting existing crops or livestock breeding) or land clearing (leading to fires and deforestation). Second, GE seeds can be viewed as a land-augmenting technology since such seeds free land to be used by complementary crops, allowing for "double cropping" after the soybean harvest.[1] Third, the GE soybean seeds also allow for better soil management, which reduces the release of greenhouse gases.

We use a dynamic difference-in-differences approach to understand the effects of pre- and post-exposure to the technology by comparing areas with high and low suitability for GE soybean seeds. Suitability for GE seeds is constructed from agro-climatic variables. Our identification strategy also explores the fact that (i) GE soybean seeds were developed primarily for the United States market and that (ii) a clear timeline was set by Brazil's judiciary for farmers to adopt GE seeds (Bustos, Caprettini, & Ponticelli, 2016; see also Section 2). The identification assumption is that high and low suitability areas would have experienced a similar trajectory in emissions absent the GE soybean seeds. Importantly, we use detailed data that allow us to measure GHG emissions for the agricultural sector as well as by selected crops (including soybean).

We see three main contributions in our paper. Our first contribution is to estimate how the productivity-enhancing GE seeds affect emissions. We start by documenting the economic impacts of the GE seeds' introduction: soybean area and output per area increased in high-suitable localities relative to less-suitable areas. The economic impacts persisted over time. Our analysis reports that GHG emissions from soybean production also increased in accordance with the augmented output. In addition, the soybean producers emitted greenhouse gases less efficiently, presenting lower productivity for a given emission level. The decreased efficiency in soybean-related emissions is consistent with leaching (possibly from the higher usage of chemical fertilizers) and oxidation of crop residue.

Beyond the *direct* effects of GE seeds on emissions, we expand the analysis to understand the *indirect* effects. The hypothesis that we put forward and test is that the GE seeds transformed local land use affecting complementary and substitute agricultural activities. Consistent with the fact that GE seeds allow for double cropping, we find an increase in the areas dedicated to complementary crops and GHG emissions related to those crops. To further unpack the indirect effects, we investigate if the increased area allocated for double cropping is associated with land-use change of existing agricultural land or land clearing.

[1] Maize, cotton, sugar cane, or rice can occupy the same plot of land since the soybean production cycle lasts approximately four months (see Section 2).

We show that the crop expansion substitutes cattle-raising pastureland, a higher-emission activity. Furthermore, our findings indicate that GE seeds technology is not accompanied by deforestation or the areas hit by fires—two major greenhouse gas emitters. When we take the GHG results together for the agricultural sector (from soybean, other crops, and cattle raising), we observe no increase in total agricultural greenhouse gas emissions. Importantly, we find that the agricultural sector as a whole emits greenhouse gases more efficiently (higher productivity for a given level of emissions). Back-of-the-envelope calculations suggest that achieving the same agricultural output level but without GE seeds would require a 25% higher emission level.

An important takeaway from our findings is that technologies can affect emissions of the targeted sector as well as indirectly affect emissions of (complementary and substitute) sectors of economic activity. Reassuringly, our results are robust to the exclusion of control variables, alternative definitions of geographical areas, and transformations of the dependent variables. In addition, the results are not driven by confounding shocks, such as commodity booms.

Our second contribution is to shed light on how technology innovations impact *carbonizing* and *decarbonizing* production responses (Da Mata & Dotta, 2022). Carbonizing production responses to a shock generate more GHG emissions. In the context of agriculture, examples of carbonizing production responses include those that cause deforestation and fires for land clearing. In turn, decarbonizing production responses to a shock reduce GHG emissions (e.g., land conversion toward lower-emission crops). Production responses to a technological shock may theoretically have positive or negative effects on GHG emissions: producers may substitute higher-emission activities for lower-emission ones, or clear land, causing deforestation. Thus, it is unclear whether technological progress in agriculture increases GHG emissions. Our findings underscore that carbonizing responses leading to deforestation and fires do not play a role. Moreover, the increase in emissions from soybean and complementary crops is offset by a decrease in high-emitting livestock—such that we do verify changes in the GHG emissions for the agricultural sector.

The third contribution lies in providing evidence on the long-standing debate in environmental economics about the Borlaug Hypothesis and Jevons Paradox (Jayachandran, 2021). The Borlaug Hypothesis states that shifts in production efficiency would be land sparing: technological changes in agriculture would reduce the pressure on the environment because less land would be needed to produce food. The Jevons Paradox points out that technological developments would promote an outward shift in the demand for land; consequently, there is a tendency to expand the production area. Our setting allows us to assess how the transformed local land use affected the final land demand and disentangle the theoretically ambiguous impact. When we analyze only the *direct* effects of the GE seeds, the evidence favors the Jevons Paradox, as there is an increase in the area dedicated to soybean production. When we take into account the direct and indirect effects, the evidence favors the Borlaug Hypothesis: acreage devoted to all crops and livestock did not change. These results reinforce the implication that indirect effects of technological advances on complementary and substitute economic activities must be considered.

Our paper connects to the extensive literature on the trade-off between economic growth and the environment (e.g., Panayotou, 2000, Grossman & Krueger, 1995), especially the strand on growth and climate change (Stern, 2008; Nordhaus, 2019). We are also related to the interdisciplinary literature on the drivers of GHG emissions (see Rosa and Dietz (2012) for meta-analysis). This literature in environmental sciences points out that economic growth and population increases will likely increase GHG emissions. The meta-analysis by Rosa and Dietz (2012) emphasizes the need to empirically demonstrate whether and how technologies can neutralize the expected rise in emissions due to growth. The interdisciplinary literature has made advances analyzing cross-country regressions (e.g., Du, Li, & Yan, 2019; Mongo, Belaïd, & Ramdani, 2021). Our paper pushes these literature forward by providing new and rare quasi-experimental evidence on the effects of technological development on emissions. Our evidence shows that GE seeds partially solve this issue: the agricultural sector present higher productivity for a given level of emission, but there are more overall GHG emissions following the steep increase in output.[2] Our paper is also unique in providing a comprehensive study on how technologies affect a set of *carbonizing* and *decarbonizing* production responses.

Our paper also relates to the broad literature on the effects of technological progress on economic growth (e.g., Caselli, 1999, Pascali, 2017). We also connect to studies on the role of agricultural technology on economic outcomes, in particular Bustos et al., 2016. Moreover, we connect to the relatively thinner branch investigating the relationship between technology and environmental outcomes, which has primarily focused on pollution (e.g., Levinson, 2009 and Shapiro & Walker, 2018) and deforestation (e.g., Angelsen and Kaimowitz (2001), Stevenson, Villoria, Byerlee, Kelley, and Maredia (2013), Assunção, Gandour, and Rocha (2015), and Carreira, Costa, and Pessoa (2022)). These studies on deforestation, like

[2]Notice that GE seeds were not conceptualized to impact emissions, as opposed to the innovations that explicitly tackle emissions ("green technology"), such as the electrification of transport and different generations of biofuels. Our study also relates to the interdisciplinary literature which focuses on the role played by the energy, transportation, and infrastructure sectors in greenhouse gas emissions (e.g., Rockström et al., 2017, Jackson et al., 2018, Schiffer & Manthiram, 2017, Di Silvestre, Favuzza, Riva Sanseverino, & Zizzo, 2018, Habert et al., 2020, and Sovacool et al., 2021).

us, find that technological progress in agriculture affects land use. However, our paper differs by studying GHG emissions (the primary cause of climate change) and assessing the effects of technological innovations on a broad set of carbonizing and decarbonizing factors (not yet studied, such as fires). We contribute then by providing a systematic exploration of an understudied topic: the relationship between technology and the main driver of climate change.

Finally, our work also relates to the literature on agricultural activities and the environment (e.g., Cerri et al., 2007, Deschênes & Greenstone, 2007, Assunção et al., 2015, Assunção, Gandour, Rocha, & Rocha, 2019, Da Mata & Dotta, 2022, Szerman, Assunção, Lipscomb, & Mobarak, 2022), and to the branch that assesses the impacts of the Green Revolution (e.g., Cleaver, 1972, Tilman, 1998, Evenson & Gollin, 2003, Frankel, 2015, Eliazer Nelson, Ravichandran, & Antony, 2019, Gollin, Hansen, & Wingender, 2021). Our study complements theses papers but breaks new ground by focusing on one the most important worldwide externalities.

This article proceeds as follows. Section 2 details the background on GE seeds and Brazil's agricultural sector. Section 3 describes the empirical strategy. Section 4 presents the data, while Section 5 reports the results. Section 6 concludes.

# 2 Background

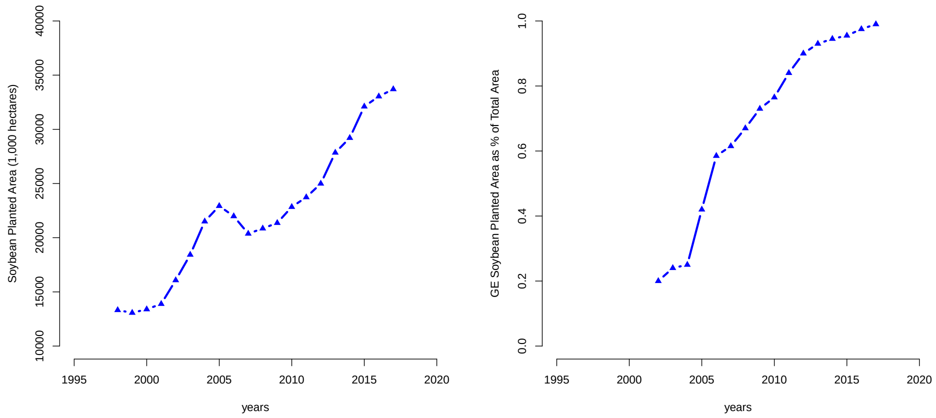
## 2.1 Genetically engineered soybean seeds

In 1996, the multinational company Monsanto released genetically engineered soybean seeds resistant to herbicides. More specifically, the GE soybean seeds were resistant to the herbicide Roundup, a brand patented by Monsanto whose active ingredient is the substance *glyphosate*. Glyphosate works by inhibiting amino acid synthesis plants need to survive and grow.

In this section, we describe how the GE seeds influence producers' decisions regarding input use, especially the demand for land. The rapid adoption of genetically modified soybean technology and the increase in the planted area indicate that soybean has become central in the Brazilian agricultural sector (see Figure 1). In our period of analysis, Brazil became the world's largest producer of soybeans with the contribution of GE seeds.[3]

[3]Brazil exports 60% of raw soybean, 50% of soybean meal and 20% of soybean oil, the three main products from soy products.

Figure 1: Soybean Planted Area and GE Soy as % of Total




(a) Soybean Area Planted (in hectares) (b) Ge Soy Seeds Planted as a Ratio

*Notes:* Panel (a) presents the evolution of soybean planted area (in 1,000 hectares) for all Brazilian municipalities from 1998 to 2020. Data comes from *Pesquisa Agrícola Municipal Mensal* (PAM-IBGE). Panel (b) presents the evolution of soybean area (as a percentage of total) which was planted using genetically engineered seeds for all Brazilian municipalities from 2002 to 2020. Data comes from CropLife (2020). Both panels include the three Southern-most states RS, SC, and PR—which we exclude from our main analysis.

**Productivity and costs**. The GE seeds increase productivity by improving seeds' accessibility to soil nutrients—GE seeds allowed farmers to use herbicides more broadly during pre- and harvest periods for weed control. As a consequence, fertilizer usage became more efficient—since GE soybean plants had no-competing access their nutrients. Before the GE seeds, weed invaders competed with soybean plants for soil nutrients and were responsible for diminishing yields. In addition, GE seeds decrease costs by reducing the need of low-skilled labor or fuel consumption for traditional farming machinery previously used for manual or mechanized weed control. Therefore, increasing soybean yields through technology is a relevant aspect of GE seed introduction.

**Double Cropping**. Apart from buffering against weeds, the technology is land-augmenting because it can free land to be used by complementary crops. The soybean pre- and post-harvest periods last approximately four months, and this short period (together with Brazil's favorable climate) created near-ideal conditions for synergetic responses by growing other crops in the soybeans' off-season. This creates incentives for the diffusion of double cropping, which may intensify the demand for land.

Rotating crops in the same field also preserves soil health and increases crop yields (Brittanica, 2022). While relatively common in temperate climate areas, the benefits from crop rotation were not completely known in tropical regions until more recently (Gonçalves, Gaudencio, Franchini, Galerani, & Garcia, 2007). In Brazil, a popular crop rotation mix is soybean-maize—farmers plan soybean in Spring and maize in Fall. Notice that double cropping can happen with other crop combinations. Since soybean is a legume, it recycles soil nitrogen and provides biological benefits to crops subsequently planted. When cropped interchangeably with plants of the grass family (such as maize, sorghum, and sugarcane), grain productivity increases by approximately 10% (EMBRAPA, 2010). Hence, the introduction of GE technology presents an important step toward using complementary crops. These increases in productivity of complementary crops allowed the country to become an important player in grain markets globally (Xu et al., 2021).

**Soil management**. In addition to controlling weeds, the substance glyphosate works as a desiccant: old plants or crops can decompose and dry more quickly (and evenly) during soil preparation. This crop-desiccant process allows for the expansion of no-till systems—an agricultural technique for planting and growing crops without tilling ("disturbing") the soil.[4] This technique does not provoke the rotting of organic matter in the soil, avoiding the release of greenhouse gases. In addition, planting over the residues of past crops/pastures can retain more water and nutrients, while the organic matter in the soil also increases. Therefore, no-till systems increased substantially due to the GE seeds because they made it possible to eliminate invader plants in the pre-planting period. Since no-tilled fields hold water and nutrients for longer, crops become more climate-resilient. The no-tilled fields also contributed to the double cropping: it allowed planting to start earlier in Spring, expanding the planting window for a second crop starting in the fall.

## 2.2 The ban on GE seeds

In 1995, before the release of Monsanto's GE seeds, the Brazilian Congress approved a bill regulating the use of genetically modified organisms (Federal Law n. 8,974). The bill established a broad set of rules regarding the production, transportation, consumption, and disposal of any modified organism. Moreover, the law created a scientific committee at the national level (CTNBio – "Comissão Técnica Nacional de Biossegurança") to assess the impacts of these organisms on human life and the environment. The committee had a dual mandate: an advisory role and the power to authorize country-wide use of genetically modified organisms.

In 1998, CTNBio issued a report granting harvesting permission and attesting that the GE technology was safe for the environment and human consumption. Shortly after the

[4] In this system, seeds are planted over the residues of previous crops by planters that cut a V-slot, place the seeds, and close the furrow.

release, a lawsuit was filed contesting the CTNBio's decision. A federal court decision accepted the lawsuit request and temporarily banned GE seeds' harvesting permission.[5] In 2000, another court decision maintained the prohibition of any commercialization of genetically modified organisms.

Anecdotal evidence points out that farmers in the Rio Grande do Sul state started using GE seeds right after CTNBio issued the favorable report. These farmers imported the seeds from Argentina and Uruguay, which had already approved the technology. After the court decision, several farmers in the Rio Grande do Sul state continued to use GE seeds. Anecdotal evidence also suggests that while the widespread use of GE seeds in Brazil did not happen, some farmers in the other two states that share borders with Argentina also imported seeds.[6] Law compliance across other states and worries about the potential dangers posed by genetically modified organisms are some factors that prevented the widespread use of GE seeds at that time.

In 2001, the Brazilian government issued a decree establishing guidelines for product labels containing genetically modified organisms. However, only in 2002 was the ban lifted. A superior court overruled the previous decision indicating no scientific evidence of the potential harms of the GE technology. On the contrary, the superior court decision referred to many international studies reassuring that the technology was deemed safe for humans and the environment. Furthermore, the superior court considered that the government resolved the alleged safety problems by issuing the decree in 2001. Shortly after, CTNBio issued a second report reinforcing the conclusions of its first investigation.[7]

### 2.3 Technology and Emissions

Our interest is to assess how technological innovation affects emissions. In the context of the expansion of the GE seeds in Brazil, there are potential effects on soybean production per se (direct effects) and other agricultural activities (indirect effects).

To test the direct effects on soybean output, we begin with the hypothesis that the pro-

[5] The first reason behind the court decision was that the overlap of roles between the CTNBio and Brazil's Ministry of the Environment presented a loophole for distinct interpretations regarding which institution should carry the *study* necessary for approving genetically modified organisms. The lawsuit demanded that the Ministry (instead of CTNBio) should conduct an official investigation of environmental impacts (called EIA-RIMA). Second, in the absence of such a study, the Brazilian legal framework argues for precaution—which backed the court's decision.

[6] The states are Paraná and Santa Catarina. By the 2001 harvest, GE seeds were already found in both states (EMBRAPA, 2003.

[7] In 2005, the Brazilian Congress approved a new bill regulating the use of genetically modified organisms to avoid further contests at the judiciary.

ductivity gains and cost reduction from GE seeds would lead to an increase in soybean *production in the extensive margin* and, therefore, increase land demand. Consequently, we would observe an increase in the area occupied by soybeans. Notice, however, that biotechnology may have a different effect: induce farmers to increase *output in the intensive margin* using the same amount of land. Assessing the increase in soybean output in either extensive or intensive margins, the effects on GHG emissions are conceptually ambivalent: an increase in emissions can happen because the higher production would be accompanied by greater use of fertilizers, but the better soil management allowed by GE seeds works toward reducing GHG emissions.

For the indirect effects, we hypothesize that GE seeds transformed local land use affecting complementary and substitute agricultural activities. Notice that a more substantial increase in soybean production at the extensive margin will generate stronger indirect effects. Consistently with the specialized literature, we expect the increased area occupied by soybeans to be allocated to double cropping during the offseason. The effects of soybean and the complementary crops are conceptually ambiguous. Soybean and complementary crops can occupy existing agricultural land (from other crops or livestock changing municipalities' production mix) or expand by clearing land (using fires and promoting deforestation). If soybean and complementary crops substitute livestock, there will be a reduction in GHG emissions since livestock is a higher emitter; animal-based food is more land intensive and higher emitted compared to grains and vegetables. By contrast, emissions will increase if soybean and complementary crops contribute to environmental degradation by promoting deforestation and fires.

## 3 Empirical Strategy

We employ a dynamic differences-in-differences design to assess the impacts of technology on emissions. Our main specification is as follows:

$$Y_{it} = \sum_{\tau=-k}^{K} \beta_\tau \cdot \left[\mathrm{A}_i \cdot (\text{ Periods Away from Event } = \tau)\right] + \phi_t + \alpha_i + \lambda X_{it} + \gamma_t W_i + \varepsilon_{it}, \quad (1)$$

where $Y_{it}$ is the outcome of interest at time $t$ (e.g., GHG emissions, pasture areas, crop areas, productivity) in municipality $i$, $A_i$ is the suitability measure to GE technology in municipality $i$, and $\phi_i$ and $\alpha_t$ are municipality and time fixed effects, respectively. The indicator variable "Periods After Event=$\tau$" takes a value of one $\tau$ periods away from the beginning of the GE soy period and zero otherwise. The vector $X_{it}$ includes time-varying geo-climatic variables (average rain and temperature), and $\gamma_t$ is the time-varying coefficient of initial socioeconomic and physical characteristics $W_i$ (illiteracy rate, population, poverty rate, and latitude and longitude). Standard errors $\varepsilon_{it}$ are clustered at the municipality level.

The parameter of interest is $\beta$, which is the effect of being exposed to the GE technology. Lower-suitability localities work as the counterfactual for the higher-suitability localities. Each coefficient $\beta_\tau$ should be interpreted as a change relative to the base period, given by the omitted coefficient $\beta_{\tau=2001}$. We use the year 2001 as the base period because a superior court lifted the GE seeds' ban in 2002.

To construct the suitability of the GE soybean seeds ($A_i$), we use the potential yield measure from FAO-GAEZ (Food and Agriculture Organization's Global Agro-Ecological Zones), which is a time-invariant measure of the maximum output given climatic (temperature, rain, and humidity) conditions. Following Bustos et al. (2016), we define $A_i$ as follows:

$$A_i = A_i^{\text{High}} - A_i^{\text{Low}} \tag{2}$$

where $A_i^c$ for $c \in \{High, Low\}$ represents the potential yield in kilograms of dry weight per hectare for soybean production given *High* and *Low* input usage under rain-fed conditions.[8] Low-input-usage yield takes into account rudimentary production techniques usually employed in subsistence-based systems, such as traditional seeds, low mechanization, and no application of plant nutrients or use of chemicals. High-input usage, on the other hand, is based on improved or high-yielding seed varieties, high mechanization, and optimal applications of nutrients and chemical pesticides.

The variable $A_i$ is suitable for measuring the genetically-engineered seed production potential for three reasons. First, the potential yield is based on climatic variables for its estimation—such as rain, temperature, and humidity. Second, the high-input potential yield considers the introduction of GE seeds in its calculation. Third, although the high-input potential yield also takes into account fertilization and mechanization, these variables have been largely unchanged over the past two decades. Therefore, our suitability measure in Equation (2) is mostly driven by the introduction of GE soy.

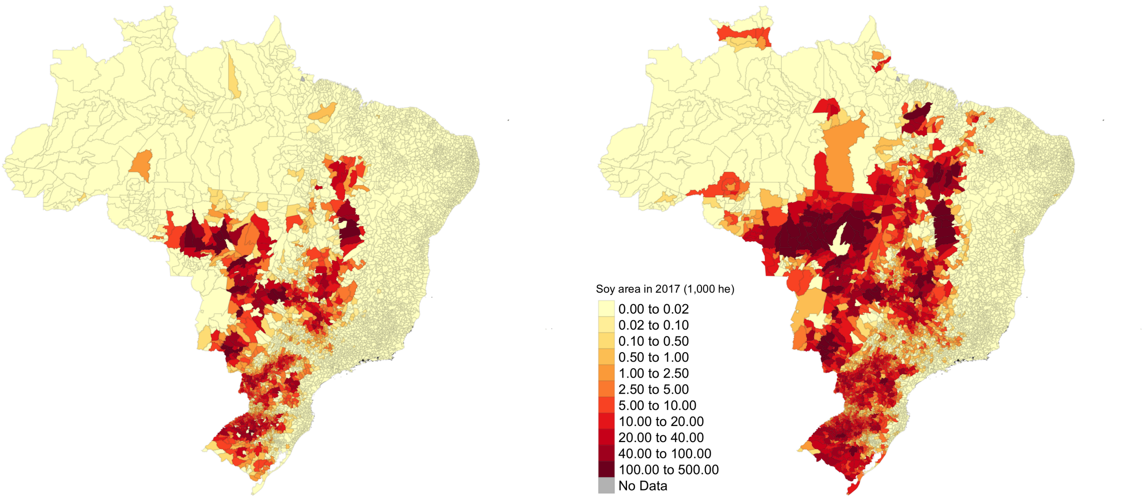
In the empirical strategy, we rely on another source of exogenous variation: the liberalization of genetically engineered soy seeds in 2002 by the judiciary. The timing of Monsanto's technology conception and the judiciary's liberalization is (arguably) exogenous to Brazil's municipalities.

Figures 1 and 2 plot the rapid adoption of GE seeds in the country during our period

[8] FAO-GAEZ's v4 provides several scenarios for agricultural production, including potential yields under irrigation usage and rain-fed conditions.

of analysis. In Figure 3, we show that the soy differential potential production ($A_i$) across Brazil could reach as far as five tons per hectare—in particular, the past six soy harvests in Brazil registered productivity between 3 and 3.5 tons per hectare (CONAB, 2022). Moreover, one can notice the central region of Brazil—where the Cerrado biome borders the Amazon rain forest—presented a 3-ton increase in differential yield, which may be considered a high incentive to augment production in this area of the country.[9]

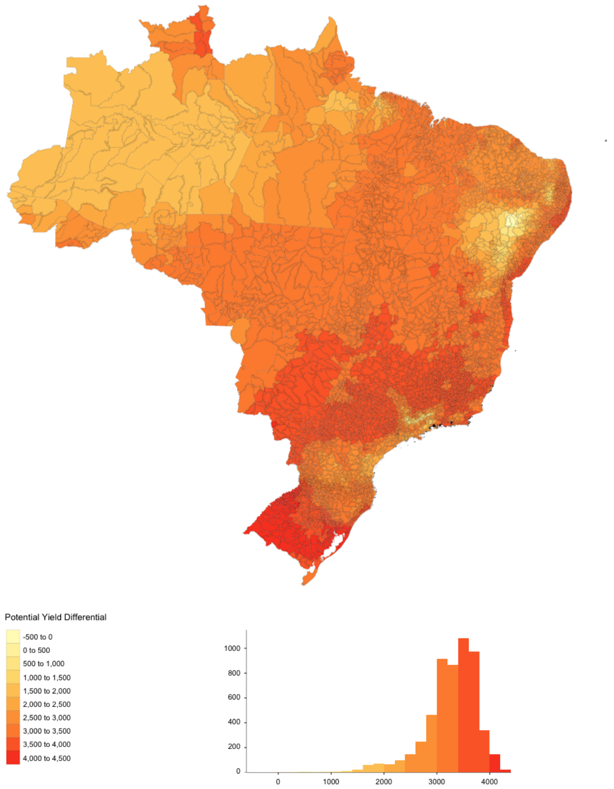
Figure 2: Soy Adoption of Soybeans Across Municipalities in Brazil (1998 and 2017)




*Notes:* These figures present municipalities which planted soybeans (both conventional and genetically engineered seeds) across Brazil in 1998 and 2017. The adoption rate is measured by soybeans planted area (in 1,000 hectares). Data comes from *Pesquisa Agrícola Municipal Mensal* (PAM-IBGE).

[9]The Amazon and Cerrado biomes represent about 73% of the country.

Figure 3: Potential Soy Production Difference ($A_i$)




*Notes:* The potential production difference ($A_i$) is given by the subtraction of low-input level potential yield from high-input level potential yield using FAO-GAEZ's v4 model data. Equation (2) provides a mathematical representation. Its unit is given in kilograms of dry weight of soybeans per hectare. The standard deviation is roughly 500 kg per hectare.

**Threats to Identification and Interpretation**. Our identifying assumption is that higher-suitability localities would have had similar trends in emissions as lower-suitability localities in the absence of the GE seeds. The next section provides a more formal analysis of preexisting differences in trends.

Some potential threats to our identification strategy and interpretation of our results could be present. First, recall the anecdotal evidence of earlier adoption of GE seeds by farmers in a few states in Brazil who imported seeds from Argentina and Uruguay (EMBRAPA, 2003). Since this event could affect the pre-trends in our analysis, we exclude from our baseline analysis these three states. We show, however, in the robustness exercises that preexisting differences are not a concern when adding the few earlier-adopting states.

Another potential concern could arise if the timing of the introduction of GE seeds coincides with other policies or shocks. Our analysis includes a period of increasing commodity prices which can be a relevant confounder (Da Mata & Dotta, 2022). We thus assess the role of the commodity boom. In addition, the Brazilian government and the private sector implemented anti-deforestation measures in the mid-2000s (Assunção et al., 2015). Therefore, we also analyze these policies' influence.

As for interpretation, notice that given the nature of our difference-in-difference analysis, we cannot estimate the effects of the technology on the levels of GHG emissions but only on the difference between higher- and lower-suitability localities.

# 4 Data

Our analysis period is 20 years, from 1998 to 2017, and the spatial unit of analysis is the municipality.[10] We work with several publicly available datasets to build a panel at the municipality-year level. To describe the data, we classify each dataset into three categories: (i) suitability to GE seeds technology, (ii) environmental and output outcomes, and (iii) additional variables.

## 4.1 Suitability to the Technology

**FAO-GAEZ.** Data on agro-climatic potential yields stem from the FAO-GAEZ database. Potential yields for soybeans are estimated using climatic conditions across Brazil (temperature, rain, and humidity). Estimates consider two different sets of input use: *high*- and *low*-input (Fischer et al., 2021). Low-input potential yields assume a subsistence-based farming system, in which the agricultural production employs traditional seed varieties, labor-intensive techniques, no use of chemicals for plant nutrition or pesticides, minimum conservation measures, and fallows to maintain soil fertility. By contrast, high-input potential yields assume advanced farm management: the farming system is market-oriented, and production relies on improved high-yielding seed varieties, high machinery usage, and optimum applications of chemicals for plant nutrition and pesticides. High and low potential yields are given in grid cells of 9 square kilometers, which we aggregate to calculate the potential soybean yield per hectare (measured in kilograms of dry weight) for each municipality. To avoid productivity gains from irrigation, we utilize rain-fed potential production

[10] Municipalities in Brazil are local autonomous political-administrative entities roughly equivalent to U.S. counties.

with average precipitation from 1961-1990. Our resulting dataset is a cross-section of high and low potential yields that we use to calculate the measure of suitability to GE seeds—see Equation 2 in Section 3.

## 4.2 Outcome Variables

**Greenhouse gas emissions**. GHG emissions data come from the *Sistema de Estimativas de Emissões e Remoções de Gases de Efeito Estufa* (SEEG). Estimates are for all municipalities combining satellite and field-collected data. Greenhouse gases include methane (CH4), nitrous oxide (N20), and other gases (e.g., perfluorocarbons, hydrofluorocarbons, sulfur hexafluoride, and nitrogen trifluoride), not just carbon dioxide (CO2). Bringing comprehensive GHG data to study the effects of technological developments is important for our setting; for instance, livestock breeding is a higher emitter of CH4, not CO2. Emissions are calculated for various economic activities, including enteric fermentation of ruminant animals, burning crops, soil fertilization, changes in land cover, burned forest residues and liming, fuel combustion, and manufacturing activities. For each municipality, we obtain data on total emissions, total agricultural emissions, and emissions for specific agricultural activities, namely: (i) individual crops (soybean, maize, rice, and sugarcane) and (ii) beef cattle. Due to data constraints, we are able to obtain GHG data only from 2000 to 2017.

**Agricultural Output**. We collect data on crop output from the Brazilian Bureau of Statistics (IBGE) at the municipality level. Data on production quantity for soybean, maize, rice, and sugarcane (in tons) come from the *Pesquisa Agrícola Municipal*, an annual survey on agricultural production. Data is collected from 1998 to 2017.

**Land use**. We assemble satellite data on land use across Brazilian municipalities using data from MapBiomas. MapBiomas processes high-resolution images (30-meter-by-30-meter pixels) from the satellite LandSat 8 to create land cover data in Brazil from 1985 to 2019. In particular, we aggregate data on the area allocated to natural forests and pasture land (for cattle-raising activities) at the municipality-year level. Furthermore, we gather data from IBGE´s *Pesquisa Agrícola Municipal* on planted areas for all the crops we work with in this paper: soybean, maize, rice, and sugar cane. Data is collected from 1998 to 2017.

**Fires data.** MapBiomas provide data on “fire scars”, which are defined as the estimated area hit by fires in a given year. MapBiomas processes data (30-meter-by-30-meter pixels) from the satellite LandSat 8 to identify the areas which experienced fires. It then aggregates the size of such areas (in hectares) across municipalities from 1985 to 2019. The fire scars data is from 1998 to 2017.

## 4.3 Additional Data

We also collect data for control variables and additional robustness checks. Data on socioeconomic variables (illiteracy, poverty, and population) come from the United Nations Development Programme' *Atlas dos Municípios* for 1991. In addition, data on average rain and average temperatures from 1998 to 2017 and latitude and longitude are from Da Mata and Resende (2020). IBGE's GDP *per capita* data at the municipality level are for the years 1999 to 2017. We also calculate cross-sectional agricultural technology controls for maize and cotton (following the same data collection procedure and specification as given in Section 4.1 for soybeans). In the heterogeneity analysis, we use two other data: a commodity exposure index from Da Mata and Dotta (2022), which uses FAO-GAEZ data, and data from the agricultural census of 1995 to build a Land Gini index based on rural property sizes and the number of properties of a given size. We describe these data in more detail in Subsection 5.6.

# 5 Results

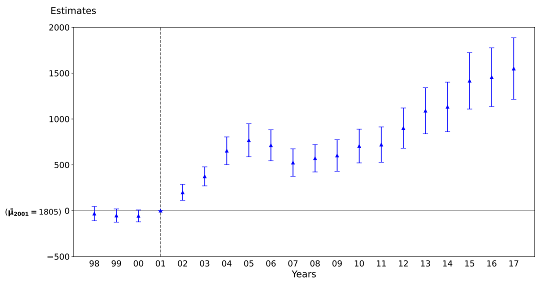
We divide our results into several parts. We begin by displaying the direct effects of technology exposure on soy (area, productivity, and GHG emissions). Then, we turn our attention to the indirect effects by assessing complementary crops, pastureland, and agriculture outcomes. We also investigate how competing mechanisms, such as deforestation and fire, may drive our results. Moreover, we display aggregate results on local GDP and and total GHG emissions. Finally, we present a relevant result: efficiency GHG emissions decrease with higher exposure to GE soy. We close this section by presenting a heterogeneity analysis for our treatment variable and for inequality in land distribution.

All of our findings are presented in Figures 4a through 13. Each plot displays the coefficients of interest as given in Equation (1) relative to the coefficient of the base year 2001. All of our specifications control for pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, longitude, latitude, and cross-section technology controls for maize and cotton. We name these our "baseline controls". In Appendix A, we also present our findings without baseline controls.

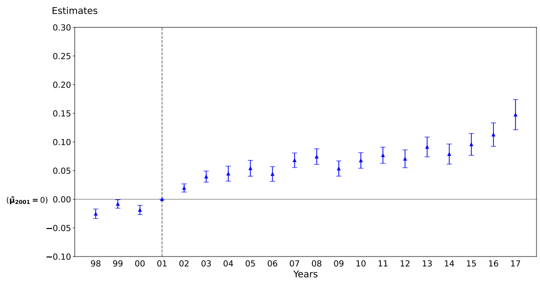
## 5.1 Soybean Sector: Direct Effects

GE soy is a High Yield Variety (HYC) since it maximizes yield if combined with proper management. In addition, the RR technology has a clear advantage over traditional cultivars in terms of direct costs associated with production and productivity gains. As a consequence, if one assumes farmers are profit-maximizing individuals, GE soy adoption should be rapid—affecting planted area. Our findings point in this direction with a strong positive response right after the ban lift. For instance, in the 2002, municipalities more exposed to the technology planted on average 250 hectares more than less exposed municipalities. Figure 4a displays these results. Notwithstanding, the results are cumulative and increase 7-fold over the next fifteen years (reaching 1,500 thousand hectares).

Figure 4: GE Soy Direct Effects




(a) Soybean Area (in hectares)

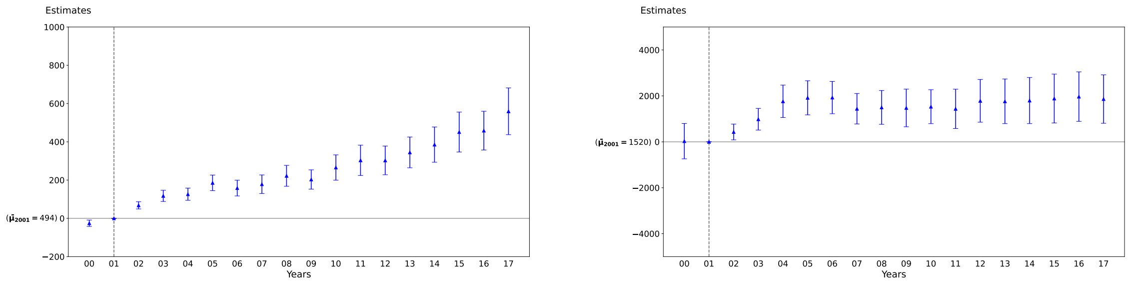



(b) Soybean Productivity (tons per hectare)

*Notes:* This figure presents the results of Equation (1) for dependent variables "Soybeans Planted Area" (Panel (a)) and "Soybean Productivity" (Panel (b)) for years 1998 to 2017. It presents the effects of soy technology, which is measured relative to 2001. Results include baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. We cluster standard errors at the municipality level.

The expansion of soybean production across Brazil raises questions about how the GE soy affects GHG emissions. As expected, the increase in soybean harvesting has lead to an increase in the absolute amount of GHG emission for the soybean industry (see Figure 5a). Although important, the absolute emission in our framework may hide the relative emission from the productivity gain. Therefore, we build a measure of efficient emission that can be understood as the amount of emission needed to deliver the current productivity level. As we have shown in Figure 4b, the productivity level has grown several folds for the municipalities with higher exposure level to the GE soy. On one hand, our results points to an increase the efficient emissions shortly after the GE soy ban lift (Figure 5b). On the other, in the long-run the efficient emissions are stable even with increasing productivity.

Figure 5: GE Soy Direct Effects




(a) Soybeans GHG Emissions

(b) GHG Soy Efficiency Emissions

*Notes:* This figure presents the results of Equation (1) for dependent variables "Soybeans GHG Emissions" and "Soybean GHG Soy Efficiency Emissions" for years 2000 to 2017. It presents the effects of soy technology, which is measured relative to 2001. GHG Emissions is measured in of CO2 equivalent. Efficiency Emission is measured in tons of CO2 equivalente per tons per hectare. Panel (a) shows soy GHG emissions. Panel (b) shows the GHG Soy Emissions (equivalenty: the GHG emission level to reach a given productivity). Results include baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. We cluster standard errors at the municipality level.

## 5.2 Complementary and Substitute Sectors: Indirect Effects

Soybean is a temporary crop. This means the processes of sowing through harvesting last approximately four months. Subsequently, farmers may explore other temporary crops in the same area, such as maize, cotton and rice. As mentioned in section 2.1, this "double cropping" is possible because Brazil, as a tropical country, generally does not freeze in the winter and some rain allows for planting crops at the beginning of the fall. In most parts of Brazil, soybeans are planted in the spring and maize (or other temporary crops) in the fall. Thus, we are interested in the effects GE soy exposure has on land cover and land use with respect to other crops.

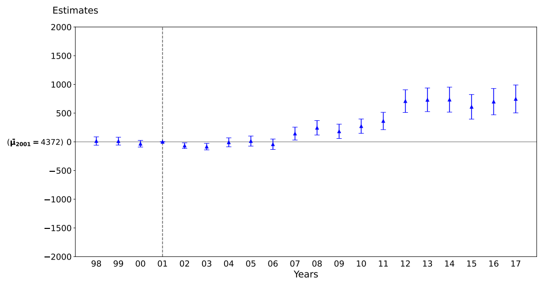
The increase in soybean area as a response to GE soy exposure might occur via two main channels. First, it may happen as an intensive margin adjustment, that is, by substituting other crops in the spring (while still allowing for their production in the fall) or expanding over less-productive pasture land. Second, it may also take place via an extensive margin of adjustment. In this case, soybean production replaces areas where previous native forests thrived (see Section 5.3). As mentioned, this is a carbonizing factor due to changes in land use (e.g., deforestation) while the intensive margin can be decarbonizing factor if—and only if—soy plantation replaces other types of soil exploration that are relatively more GHG-emitting. We focus below on showing the effects of genetically engineered soybean exposure on areas of complementary crops, pastureland, agriculture, and natural forests.

Figure 6 displays the results of GE soy on the variables of interest mentioned above. Our findings show that complementary crop areas (maize, rice, and sugar cane) increase substantially in more exposed municipalities (Panel a). Additionally, the intensive margin prevails over the extensive margin, since we show that pastureland presents a strong negative response to GE soy potential yield (Panel c), and there is no evidence of an increase in the area dedicated to agriculture (Panel e). Moreover, while complementary crops and agricultural productivity increases (Panels b and f), there is no evidence Beef Cattle productivity change (Panel d). On average, our results show that livestock area is decreasing, while the productivity is stable (Panels c and d) and agriculture area is increasing (Panel e).

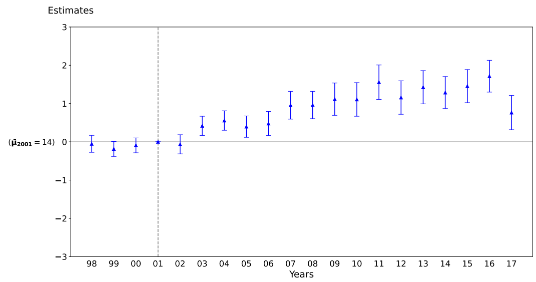
The substitution effect described above—from livestock to farming—is reinforced by the productivity change observed within different land usages that are taken into account in our analysis.This suggests that farmers who opted on reducing pasture areas did so accompanied by a decrease in cattle herd size in municipalities more exposed to GE soy. In addition, our results show that agriculture productivity is driven almost exclusively by soybean and complementary crop productivity—, despite the relative importance of cattle raising activities in Brazil.

Altogether, these results indicate relevant *decarbonizing* factors in terms of agricultural productivity. The GE soy provided that farmers could produce more in a given area. Thus, avoiding further deforestation. Moreover, the mix of products—shifting from livestock to farming—also presents an improvement in terms carbon footprint, an issue we discuss next.

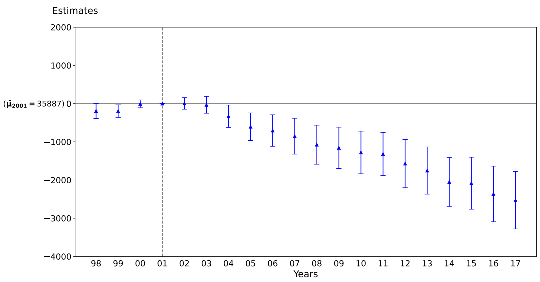
Figure 6: Indirect Effects of GE Soy Exposure: Area and Productivity



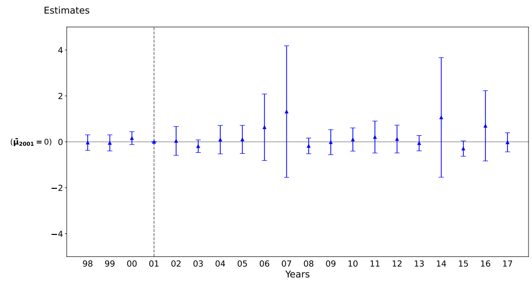

(a) Complementary Crops Area



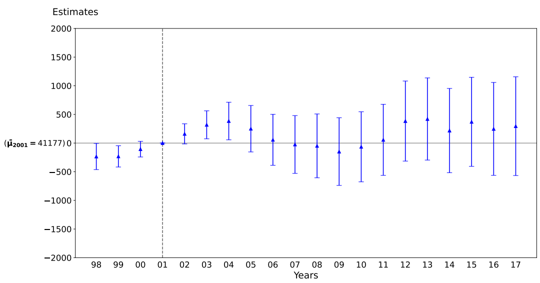

(b) Complementary Crops Productivity



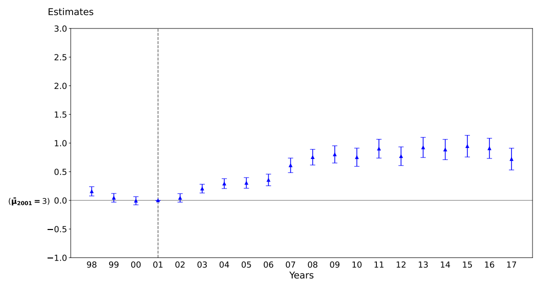

(c) Pasture Land




(d) Beef Cattle Productivity




(e) Agriculture Area

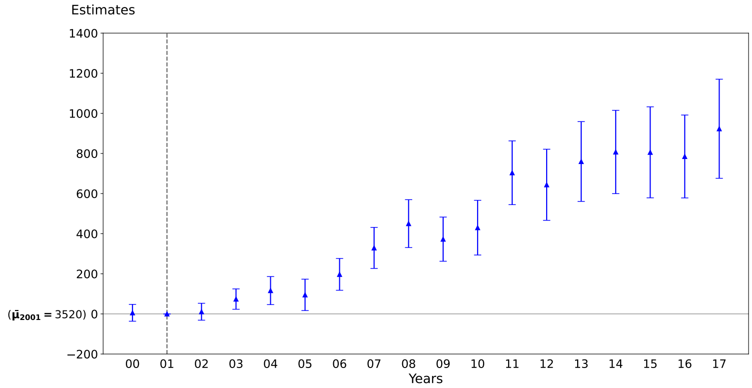



(f) Agriculture Productivity

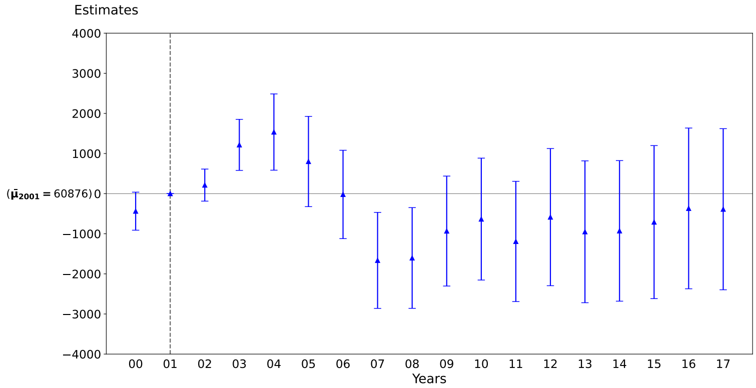
*Notes:* This figure presents the results of Equation (1) for dependent variables: “Complementary Crops Area", “Pasture Land", and “Agriculture Area". Area is measured in hectares. Productivity is measured in tons per hectare. Panel (a) shows the impacts of technology exposure on complementary crops area. Panel (b) shows the impacts of technology exposure on complementary crop productivity. Panel (c) displays the results on pasture land. Panel (d) displays the results on beef cattle productivity. Panel (e) shows the effects on agriculture area. Panel (f) shows the effects on agricultural productivity. All dependent variables are measured in hectares. Results include baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. We cluster standard errors at the municipality level.

It is commonly accepted that economic expansion usually leads to increases in GHG emissions. However, our results indicate that it is not always the case if growth is fostered by a technology that replaces activities that emit relatively less GHG. Figure 7 below suggests this is precisely the case for the genetically engineered soy technology. We identify strong effects on soybean and complementary crop emissions as shown in Panels (a) and (b), a mechanical effect from increasing area and total production—productivity increases for both variables. On the other hand, there is no evidence of change in beef cattle emissions in Panel (c). Recall pasture area decreases as a response to GE soy, and the quantity of cattle heads in exposed municipalities falls as well. As result, aggregate agriculture emissions in Panel (d) show no relevant effects.

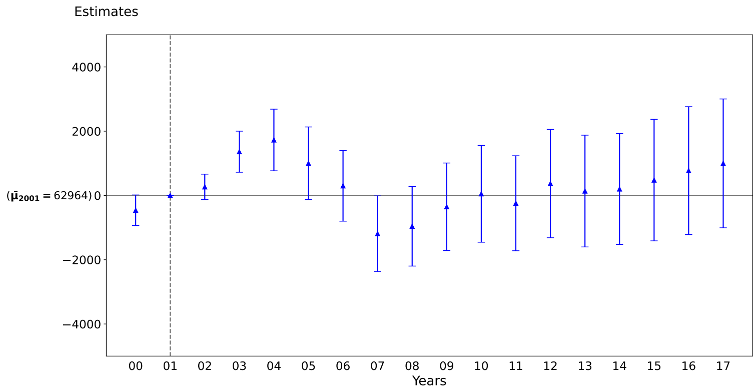
Figure 7: Indirect Effects of GE Soy Exposure: GHG Emissions




(a) Complementary Crops GHG Emissions




(b) Beef Cattle GHG Emissions



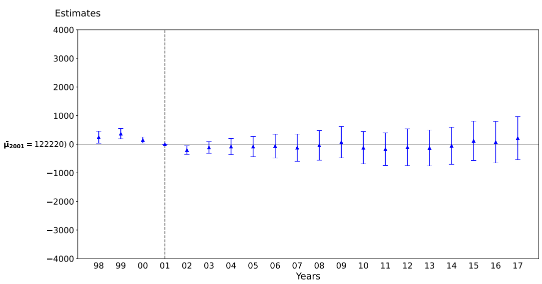

(c) Agriculture GHG Emissions

*Notes:* This figure presents the results of Equation (1) for dependent variables "Complementary Crops GHG Emissions", "Beef Cattle GHG Emissions", and "Agriculture GHG Emissions". All variables are in tons of CO2 equivalente. Panel (a) shows the impacts of technology exposure on complementary crop GHG Emissions. Panel (b) displays the results on beef cattle GHG Emissions. Panel (c) shows the effects on agricultural GHG Emissions. Results include baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. We cluster standard errors at the municipality level.

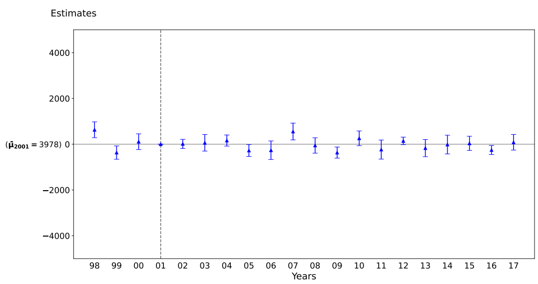
## 5.3 Competing Mechanisms: Impacts on Forests and Fires

One can reasonably argue that the GE soy could have promoted change in land use (deforestation) with fires being the most common method used to "open" new areas for agriculture —for instance, Menezes, Pucci, Mourão, and Gandour (2021) demonstrate that fires are used as a first step in the deforestation process in the Amazon region.Thus, fires are a central issue when it comes to clearing new land Reassuringly, we find no evidence of changes in natural area and fires – see Figure 8.

Figure 8: Effects of GE Soybeans Exposure on Natural Forest and Area Hit by Fires




(a) Natural Forest Area (in hectares)




(b) Area hit by Fires (in hectares)

*Notes:* This figure presents the results of Equation (1) for dependent variables "Natural Forest Area" and "Area hit by Fires". Panel (a) presents the effects of soy technology exposure on natural forest area and Panel (b) shows the impacts of GE soy on fire scars—areas hit by fires. All dependent variables are measured in hectares. Results include baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. We cluster standard errors at the municipality level.

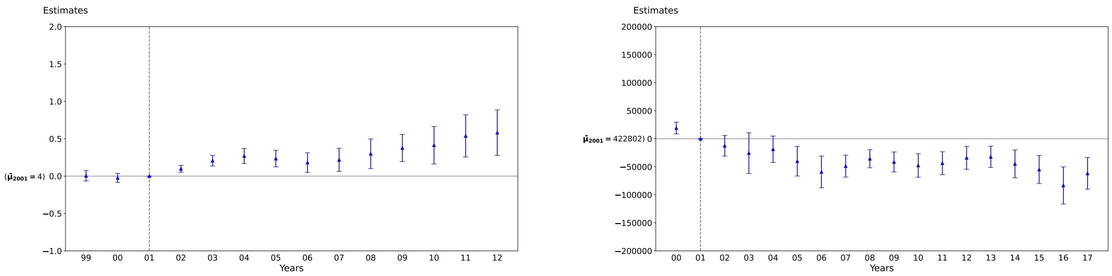
Taken together with the previous results, we conclude that municipalities more exposed to GE soy underwent a decrease in pasture areas while complementary crop areas increased and agricultural areas remained constant. As a consequence, natural forest areas were not impacted by the introduction of GE technology. In fact, a substitution effect took place in terms of soybeans and pasture land. Particularly, notice that 15 years after the introduction of GE soy, the change in pasture land is approximately 2 thousand hectares relative to 2001 levels for the average municipality—whereas the increase in soybean area was about 1.5 thousand hectares, as shown in Section 4a. This characterizes a strong *decarbonizing* factor since soybean production emits much fewer greenhouse gases than bovine production.

## 5.4 Aggregate Effects

The genetically engineered technology virtually allowed soybeans to be planted all over the Brazilian territory. It affected local economic growth differently across the country, changing the development path for cities more exposed to GE soy. In Figure 9a, we find strong evidence that GE soy changed local economic growth because it added roughly R$ 0.5 thousand per capita (approximately 15%) after ten years. It is a substantial rise in per capita income and likely comes from the productivity spillovers of the genetically modified soybeans.

In contrast, one would expect GHG emission to rise in response to GE soy exposure and a growing GDP per capita. However, that is not the case as we show in Figure 9b. In fact, total GHG emissions respond negatively to the introduction of the GE soy technology—indicating that municipalities more exposed to the technology reduced their carbon footprint. This is a relevant result because it suggests agricultural technology may be able to enrich citizens while reducing their associated total GHG emissions.

Figure 9: Aggregate Effects of GE Soybeans on GDP Per Capita and Gross Emissions




(a) GDP Per Capita in Brazilian *reais* (b) Total Gross GHG Emissions (tons of CO2eq.)

*Notes:* This figure presents the results of Equation (1) for dependent variables "Gross Domestic Product (GDP) per capita" and "Total Gross GHG Emissions". GDP per capita is expressed in Brazilian *reais* (nominal values in R$ 1,000) and range from 1999 to 2012. Results include baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. We cluster standard errors at the municipality level.

## 5.5 Agriculture Efficient Emissions

By themselves, the above results already provide interesting insights into how GHG emissions have been impacted by technology. On one hand, as expected, soybean and complementary crop emissions have risen. On the other, beef cattle emissions remained relatively unaffected, steering agriculture emissions to behave similarly. This result is relevant because aggregate food production increased while aggregate GHG emissions remained constant—implying fewer emissions per unit of production.

Furthermore, we assess whether the genetically engineered soybean seed had effects on what we name “efficiency emissions". This a measure that considers total GHG emissions per unit of production (in tons) per hectare. It yields the amount of emissions necessary to achieve the current productivity level and it is a paramount indicator of GHG-production efficiency. In summary, smaller magnitudes represent a higher efficiency for production in terms of greenhouse gas emissions—since fewer emissions are necessary to reach that productivity level.

There are two main mechanisms at work when considering these efficiency emissions. As previously mentioned, the RR technology allowed GE seeds to be planted country-wide rapidly, even in less productive areas. Hence, in the short-run one should expect efficiency to remain relatively stable. In the long run, however, as the GE technology gained traction and farmers applied it more optimally, one should expect improvements in GHG emissions. As shown in Figure 10, this is exactly what took place in Brazil. As production expands over new land for soybean production in the first 10 years (replacing pastureland or other crops), there is no gain in terms of efficient emissions. However, the effects appear as gains of scale and productivity consistently reduce the GHG emission-to-productivity ratio over the remaining years of our analysis.

Figure 10: Effects of GE Soybeans Exposure on GHG Agriculture per Productivity (tons of CO2eq. per tons per hectare)

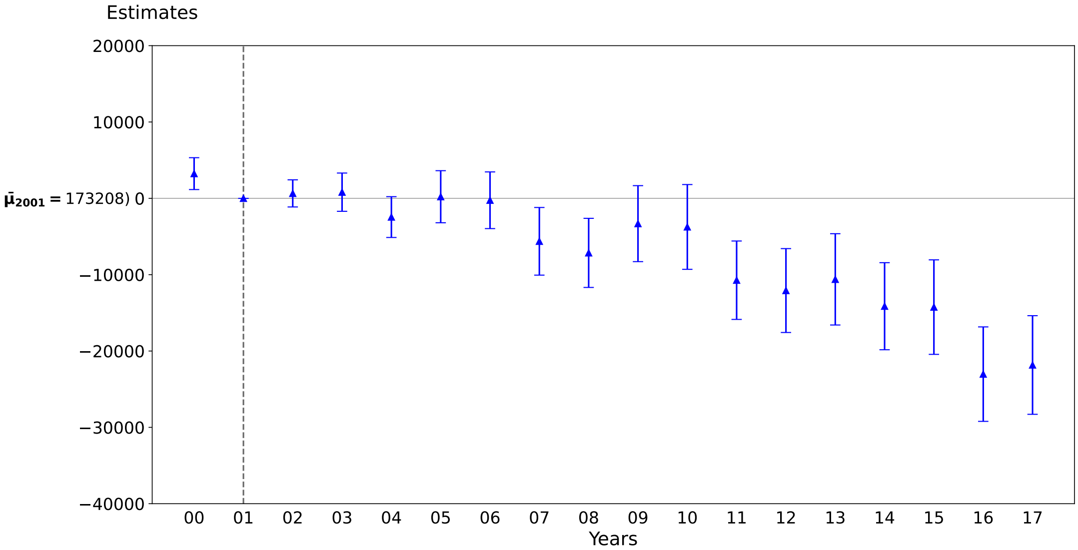



Figure 11: GHG Efficiency Emissions (tons of CO2eq. per tons per hectare)

*Notes:* This figure presents the results of Equation (1) for dependent variables "Soybean GHG Emissions Per Productivity" and "Agriculture GHG Emissions Per Productivity". Whe sow the impacts of soy technology on agriculture GHG emissions per productivity level. Results include baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. We cluster standard errors at the municipality level.

## 5.6 Heterogeneity Analysis

Given all of the above, we conduct two relevant heterogeneity analyses focused on GE soy technology and land inequality. Our main focus is to shed light on the mechanisms behind the main results described thus far.

### 5.6.1 GE Soy Technology

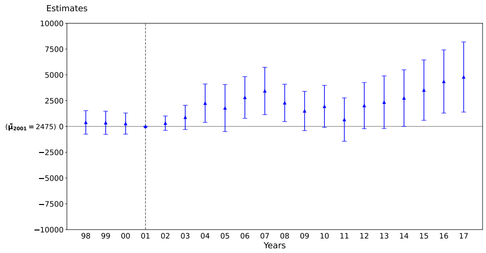
We first explore the heterogeneity in our treatment variable GE soy—given by Equation (2). We divide municipalities above and below the median of our GE soy variable and perform our baseline analysis on soy planted area, complementary crop area, natural forest area, and pasture area. Figure 12 displays the results. One can notice that municipalities above the median differ from their counterparts in two main respects: (i) natural forest areas are not statistically impacted by GE soy, and (ii) such localities replace pasture areas with soybean and other complementary crops. This indicates that our results describe in the sections above are driven mainly by municipalities which present a higher production potential with genetically engineered soybeans.

### 5.6.2 Land Gini Index

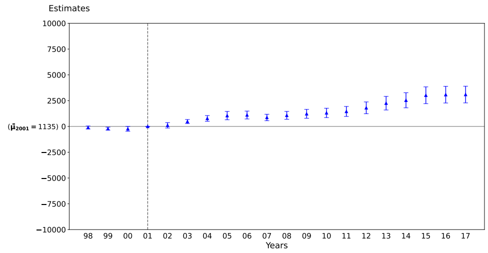
We also seek to understand the role played by smaller and bigger rural properties when it comes to the effects we identified in the previous sections. Soybean production is susceptible to gains of scale, which might suggest the underlying mechanisms for different property sizes may be distinct. We thus investigate how municipalities with higher land inequality are impacted by GE soy technology.

We first build a Land Gini Index using data from the Brazilian agricultural census of 1995. We utilize as inputs the number of farms of various size intervals and the aggregate size (in hectares) of each interval at the municipality level. Next, we separate municipalities above and below the median of the Land Gini Index and perform our analysis on soy planted area, complementary crop area, natural forest area, and pasture area. Figure 13 shows our results. In summary, municipalities with a high land inequality—associated with a greater number of bigger farms—present a similar behavior as the one described in the previous subsection in response to GE soy. The prevailing mechanism is again the substitution of pastureland with soybean areas—with no significant effects on natural forests.

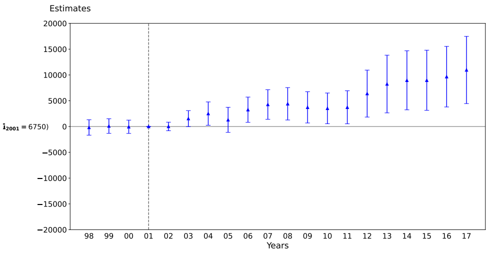
Figure 12: Heterogeneity Analysis for Treatment Variable $A$: Municipalities Above and Below the Median



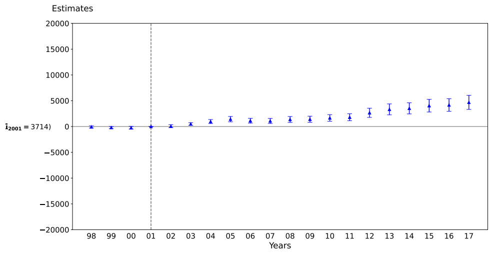

(a) Above Median: soy planted area



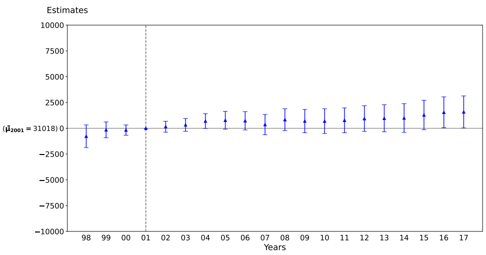

(b) Below Median: soy planted area



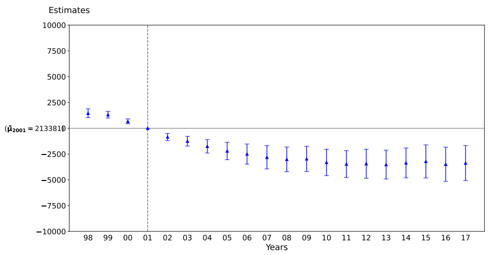

(c) Above Median: complementary crop area



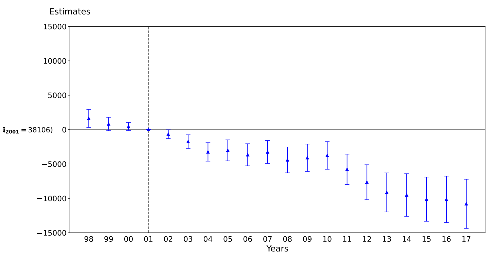

(d) Below Median: complementary crop area



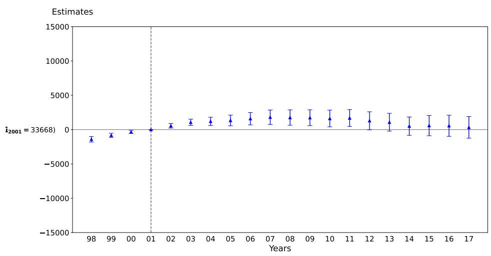

(e) Above median: natural forest area




(f) Below median: natural forest area



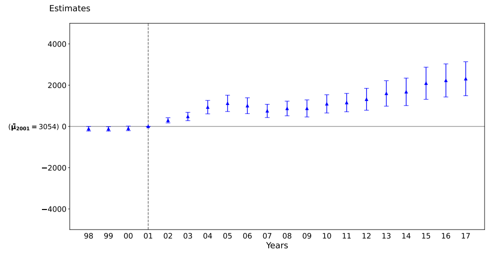

(g) Above median: pasture area



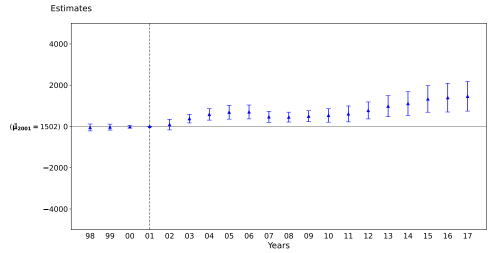

(h) Above median: pasture area

*Notes:* This figure presents the results of Equation (1) for dependent variables above and below the median for Treatment $A$: "Soybeans Planted Area", "Complementary Crop Area", "Natural Forest Area", "Pastureland". Panels (a) and (b) assess the impacts on soy planted area. Panels (c) and (d) on complementary crop area. Panels (e) e (f) on natural forest cover. Panels (g) and (h) on pasture area. All outcomes are in hectares. All results presented do not include baseline controls nor the Southern-region states (RS, SC, and PR). We cluster standard errors at the municipality level.

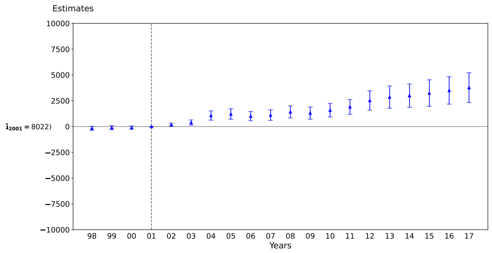
Figure 13: Heterogeneity Analysis Using a Land Gini Index: Municipalities Above and Below the Median



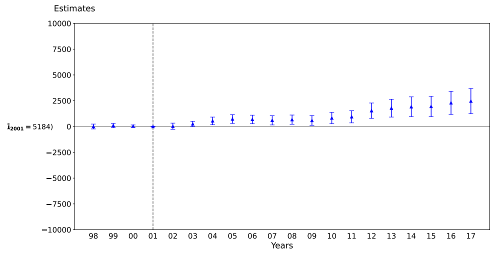

(a) Above Median: soy planted area



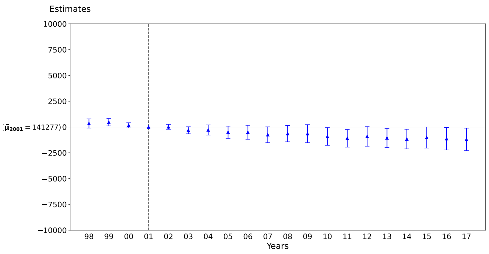

(b) Below Median: soy planted area



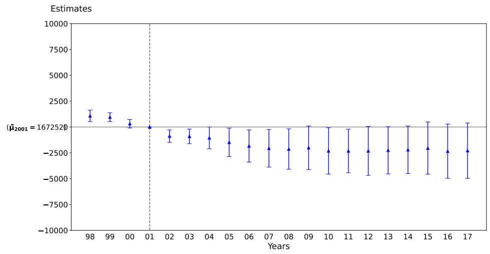

(c) Above Median: complementary crop area



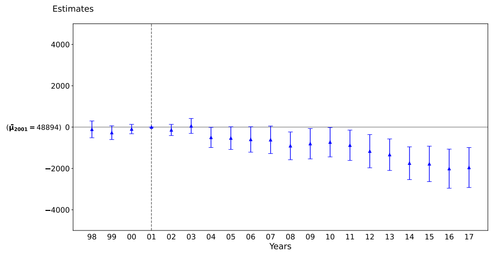

(d) Below Median: complementary crop area



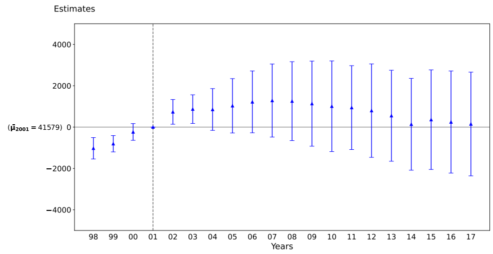

(e) Above median: natural forest area




(f) Below median: natural forest area




(g) Above median: pasture area




(h) Above median: pasture area

*Notes:* This figure presents the results of Equation (1) for dependent variables above and below the median using the Land Gini Index: “Soybeans Planted Area", “Complementary Crop Area", “Natural Forest Area", “Pastureland". Panels (a) and (b) assess the impacts on soy planted area. Panels (c) and (d) on complementary crop area. Panels (e) e (f) on natural forest cover. Panels (g) and (h) on pasture area. All outcomes are in hectares. All results presented do not include baseline controls nor the Southern-region states (RS, SC, and PR). We cluster standard errors at the municipality level.

## 5.7 Robustness

We run several robustness checks. In our exercises we (often) follow a similar format and for each robustness we (often) show the effects on (i) soybean planted area, (ii) complementary crop area, (iii) pastureland, (iv) natural forest area, (v) agriculture GHG emissions, and (vi) agriculture efficiency emissions.

**No Controls.** In Appendix Figure A.1 we display results without controls—and without the Southern states RS, SC, and PR. As one can notice, all our results remain valid. An issue that arises in this empirical exercise is the emergence of pre-trends in some of the results (e.g., pastureland, natural forest area).

**All Municipalities.** We also provide results for all Brazilian municipalities—including localities from Southern states RS, SC, and PR—with and without controls. We display the results in Appendix Figure A.2. As one can notice, all our outcomes remain relevant (again, with the emergence of some pre-trends).

**Log-Log.** Appendix Figure A.3 displays the elasticity results. Using the logarithm transformation largely maintains our main results.

**Minimum Comparable Areas.** We also test our results with Minimum Comparable Areas (MCAs). We display our results in Appendix Figure A.4; our results remain largely robust.

**Local Labor Markets.** We use IBGE's definition of micro-regions to test for effects on larger geographical areas which share a common labor market. IBGE defines 510 units of micro-regions across Brazil. Appendix Figure A.5 shows the results.

**Confounders.** We use the commodity boom measure by Da Mata and Dotta (2022) to assess the possibility of either (i) commodity prices or (ii) agricultural suitability be driving our results. We provide checks using soy planted area as our main outcome variable. We first display soybean planted area using agricultural suitability (time-invariant) and commodity exposure as controls (time-varying)—see Panel (a). Notice GE soy still impacts soy planted area with such controls, suggesting they do not eliminate the effects of technology on new soy areas. We then compare results by subsetting municipalities above and below the median according to the commodity exposure measure and performing our analysis using our baseline approach (Panels (b) and (d)) and our baseline approach with commodity controls (Panels (c) and (d)). As one can notice in Figure A.6 our results remain relatively unaffected.

# 6 Conclusion

We study the effects of agricultural technology on environmental variables, with a particular emphasis on GHG emissions. This has become an important issue over the past decades due to a rising concern with climate change. We investigate how the introduction of genetically engineered soybean impacted land cover and use, crop areas, pastureland, and greenhouse gas emissions. Our findings draw a positive perspective over the alleged trade-off between economic growth and the environment.

We show that the rise of the GE soy technology first led to an expansion in planted areas for soybeans. We then seek to understand whether this expansion was related to land conversion from natural forests or previously-cleared areas—such as pastureland or other crop areas. We show that genetically engineered soy is associated with the latter, and most land conversion comes from pasture land. This result is relevant because it displays how technology contributes to increasing productivity of historically-low productive areas—like extensive pastures. Our results on the effects of GE soy on areas hit by fires reinforce such outcomes, since fires are usually a first step towards more deforestation. Moreover, we demonstrate that GE soy technology also affects agricultural productivity positively: complementary crops presented a sharp rise in localities more exposed by GE soy while cattle raising activities did not show statistically significant outcomes. Qualitatively, farmers became capable of expanding farming through pastureland conversion and double-cropping while likely reducing their cattle numbers proportionally.

We then investigate the effects of soy technology on greenhouse gas emissions. Our results remain consistent with the above: while emissions related to soy and complementary crop production increased substantially, beef cattle and agriculture emissions did not respond significantly to the introduction of GE soy. However, a paramount result emerges when we take into account the greenhouse gas emissions needed to achieve a given productivity level: they fall as a response to GE soy. Hence, these “efficiency emissions" show fewer emissions are required for the same level of productivity, suggesting a strong decarbonizing characteristic of soybean technology.

Next, we study the aggregate effects of the introduction of GE soybeans: we first show there was a positive response in terms of GDP per capita. The latter likely comes from the productivity impacts of GE soy, leading to higher labor productivity. This has strong spillover effects on local economies, especially those more associated with agricultural activities and soy in particular. However, unexpectedly, total GHG emissions presented a negative response to GE soy. This result likely comes from the fact that municipalities more exposed to soy technology specialized in soy and crop production away from bovine production, thus having a strong aggregate effect.

Finally, we seek to understand the driving forces behind our results in terms of exposure to GE soy technology and land inequality. We perform a heterogeneity analysis dividing municipalities above and below the median for such variables. Our results suggest the underlying mechanisms are more present in municipalities with a higher exposure to soybean technology and with more unequal land distributions—often associated with bigger properties.

Our results shed light on relevant matters for the near future, especially regarding how food production may increase while concomitantly reducing its environmental footprint. New technologies such as the genetically engineered soybean may assist in such endeavor, providing high-quality protein to the world, converting under-utilized pastureland into more productive cropland, improving crop productivity, and avoiding further deforestation.

# References


Angelsen, A., & Kaimowitz, D. (2001). *Agricultural technologies and tropical deforestation.* CABi.

Assunção, J., Gandour, C., & Rocha, R. (2015). Deforestation slowdown in the brazilian amazon: prices or policies? *Environment and Development Economics*, *20*(6), 697–722. doi: 10.1017/S1355770X15000078

Assunção, J., Gandour, C., Rocha, R., & Rocha, R. (2019, 11). The Effect of Rural Credit on Deforestation: Evidence from the Brazilian Amazon. *The Economic Journal*, *130*(626), 290-330. Retrieved from https://doi.org/10.1093/ej/uez060 doi: 10.1093/ej/uez060

Brittanica. (2022). *Crop Rotation.* Retrieved 2022-06-06, from https://www.britannica.com/topic/crop-rotation

Burrell, A., Evans, J., & De Kauwe, M. (2020). Anthropogenic climate change has driven over 5 million km2 of drylands towards desertification. *Nature Communications*, *11*, 3852.

Bustos, P., Caprettini, B., & Ponticelli, J. (2016, June). Agricultural productivity and structural transformation: Evidence from brazil. *American Economic Review*, *106*(6), 1320-65. Retrieved from https://www.aeaweb.org/articles?id=10.1257/aer.20131061 doi: 10.1257/aer.20131061

Carreira, I., Costa, F. J. M., & Pessoa, J. P. (2022). *The deforestation effects of trade and agricultural productivity in brazil* (SocArXiv No. hy3np). Center for Open Science. Retrieved from https://EconPapers.repec.org/RePEc:osf:socarx:hy3np

Caselli, F. (1999, March). Technological revolutions. *American Economic Review*, *89*(1), 78-102. Retrieved from https://www.aeaweb.org/articles?id=10.1257/aer.89.1.78 doi: 10.1257/aer.89.1.78

Cerri, C. E. P., Sparovek, G., Bernoux, M., Easterling, W. E., Melillo, J. M., & Cerri, C. C. (2007, 02). Tropical Agriculture and Global Warming: Impacts and Mitigation Options. *Scientia Agricola*, *64*, 83 - 99.

Cleaver, H. M. (1972). The contradictions of the green revolution. *The American economic review*, *62*(1/2), 177–186.

CONAB. (2022). *Série Histórica das Safras.* Conab Companhia Nacional do Abastecimento. Retrieved 2022-05-20, from https://www.conab.gov.br/info-agro/safras/serie-historica-das-safras?start=30

Conte, B., Desmet, K., Nagy, D. K., & Rossi-Hansberg, E. (2020, December). *Local sectoral specialization in a warming world* (Working Paper No. 28163). National Bureau of Economic Research.

CropLife. (2020). *O Cultivo de Plantas Transgênicas no Brasil.* Retrieved 2022-06-06, from https://croplifebrasil.org/noticias/plantas-transgenicas-no-brasil/

Da Mata, D., & Dotta, M. (2022). *Commodity Booms and The Environment* (SSRN Working Paper). Retrieved from https://ssrn.com/abstract=3900793

Da Mata, D., & Resende, G. (2020). Changing the Climate for Banking: The Economic Effects of Credit in a Climate-Vulnerable Area. *Journal of Development Economics*, *146*, 102459.

Deschênes, O., & Greenstone, M. (2007, March). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *American Economic Review*, *97*(1), 354-385.

Di Silvestre, M. L., Favuzza, S., Riva Sanseverino, E., & Zizzo, G. (2018). How decarbonization, digitalization and decentralization are changing key power infrastructures. *Renewable and Sustainable Energy Reviews*, *93*, 483-498. Retrieved from https://www.sciencedirect.com/science/article/pii/S1364032118304283 doi: https://doi.org/10.1016/j.rser.2018.05.068

Du, K., Li, P., & Yan, Z. (2019). Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data. *Technological Forecasting and Social Change*, *146*(C), 297-303.

Eliazer Nelson, A. R. L., Ravichandran, K., & Antony, U. (2019). The impact of the green revolution on indigenous crops of india. *Journal of Ethnic Foods*, *6*(1), 1–10.

EMBRAPA. (2003). *Cronologia do Embargo.* Embrapa Soja. Retrieved 2022-05-20, from https://www.embrapa.br/documents/1355202/1529289/Cronologia_do_Embargo_Judicial_da_Soja_Transg%EAnica.pdf/a6c56275-aaf6-496f-b3c5-2670491ae0e6#:~:text=A%20primeira%20apreens%C3%A3o%20de%20soja,e%20a%20defesa%20dos%20produtores.

EMBRAPA. (2010). *Rotação de Culturas Garante 10% de Aumento de Produtividade.* Retrieved 2022-06-06, from https://www.embrapa.br/busca-de-noticias/-/noticia/18117874/rotacao-de-culturas-garante-10-de-aumento-de-produtividade--

Evenson, R. E., & Gollin, D. (2003). Assessing the impact of the green revolution, 1960 to

2000. *science*.

FAOSTAT. (2020). *Countries by Commodity.* Food and Agriculture Organization. Retrieved 2020-12-21, from http://www.fao.org/faostat/en/#rankings/countries_by_commodity

Fischer, G., Nachtergaele, F., van Velthuizen, H., Chiozza, F., Franceschini, G., Henry, M., ... Tramberend, S. (2021). *Global Agro-Ecological Zones v4 – Model documentation* [Technical Paper]. Food and Agriculture Organization.

Frankel, F. R. (2015). India's green revolution. In *India's green revolution.* Princeton University Press.

Gollin, D., Hansen, C. W., & Wingender, A. M. (2021). Two blades of grass: The impact of the green revolution. *Journal of Political Economy*, *129*(8), 2344–2384.

Gonçalves, S., Gaudencio, C., Franchini, J., Galerani, P., & Garcia, A. (2007). Rotação de Culturas. *Circular Técnica 45*, *1*(1), 1-10. Retrieved from https://ainfo.cnptia.embrapa.br/digital/bitstream/CNPSO-2009-09/27612/1/circtec45.pdf

Grossman, G. M., & Krueger, A. B. (1995, 05). Economic Growth and the Environment*. *The Quarterly Journal of Economics*, *110*(2), 353-377. Retrieved from https://doi.org/10.2307/2118443 doi: 10.2307/2118443

Habert, G., Miller, S. A., John, V. M., Provis, J. L., Favier, A., Horvath, A., & Scrivener, K. L. (2020). Environmental impacts and decarbonization strategies in the cement and concrete industries. *Nature Reviews Earth & Environment*, *1*(11), 559–573.

IPCC. (2021). Summary for Policymakers. In V. Masson-Delmotte et al. (Eds.), *Climate change 2021: The physical science basis. contribution of working group i to the sixth assessment report of the intergovernmental panel on climate change.* Cambridge University Press.

Jackson, R. B., Le Quéré, C., Andrew, R., Canadell, J. G., Korsbakken, J. I., Liu, Z., ... Zheng, B. (2018). Global energy growth is outpacing decarbonization. *Environmental Research Letters*, *13*(12), 120401.

Jayachandran, S. (2021). *How economic development influences the environment* (Tech. Rep.). National Bureau of Economic Research.

Levinson, A. (2009, December). Technology, international trade, and pollution from us manufacturing. *American Economic Review*, *99*(5), 2177-92. Retrieved from https://www.aeaweb.org/articles?id=10.1257/aer.99.5.2177 doi: 10.1257/aer.99.5.2177

Menezes, D., Pucci, R., Mourão, J., & Gandour, C. (2021). *The Relationship between Forest*

*Fires and Deforestation in the Amazon: Phenomena Are More Closely Related in Rural Settlements and in Occupied Public Lands* (CPI Insight). Climate Policy Initiative.

Mongo, M., Belaïd, F., & Ramdani, B. (2021). The effects of environmental innovations on co2 emissions: Empirical evidence from europe. *Environmental Science Policy*, *118*, 1-9.

Nordhaus, W. (2019). Climate Change: The Ultimate Challenge for Economics. *American Economic Review*, *109*(6), 1991-2014.

Panayotou, T. (2000). *Economic Growth and the Environment* (CID Working Papers No. 56). Center for International Development at Harvard University.

Pascali, L. (2017, September). The wind of change: Maritime technology, trade, and economic development. *American Economic Review*, *107*(9), 2821-54. Retrieved from https://www.aeaweb.org/articles?id=10.1257/aer.20140832 doi: 10.1257/aer.20140832

Poore, J., & Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. *Science*, *360*(6392), 987-992. Retrieved from https://www.science.org/doi/abs/10.1126/science.aaq0216 doi: 10.1126/science.aaq0216

Rockström, J., Gaffney, O., Rogelj, J., Meinshausen, M., Nakicenovic, N., & Schellnhuber, H. J. (2017). A roadmap for rapid decarbonization. *Science*, *355*(6331), 1269-1271. Retrieved from https://www.science.org/doi/abs/10.1126/science.aah3443 doi: 10.1126/science.aah3443

Rosa, E., & Dietz, T. (2012). Human Drivers of National Greenhouse-Gas Emissions. *Nature Climate Change*, *2*, 581.

Schiffer, Z. J., & Manthiram, K. (2017). Electrification and decarbonization of the chemical industry. *Joule*, *1*(1), 10-14. Retrieved from https://www.sciencedirect.com/science/article/pii/S2542435117300156 doi: https://doi.org/10.1016/j.joule.2017.07.008

Shapiro, J. S., & Walker, R. (2018, December). Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade. *American Economic Review*, *108*(12), 3814-54. Retrieved from https://www.aeaweb.org/articles?id=10.1257/aer.20151272 doi: 10.1257/aer.20151272

Sovacool, B. K., Bazilian, M., Griffiths, S., Kim, J., Foley, A., & Rooney, D. (2021). Decarbonizing the food and beverages industry: A critical and systematic review of developments, sociotechnical systems and policy options. *Renewable and Sustainable Energy Reviews*, *143*, 110856. Retrieved from https://www.sciencedirect

.com/science/article/pii/S1364032121001507 doi: https://doi.org/10.1016/j.rser.2021.110856

Stern, N. (2008). The Economics of Climate Change. *American Economic Review*, *98*(2), 1-37.

Stevenson, J. R., Villoria, N., Byerlee, D., Kelley, T., & Maredia, M. (2013). Green revolution research saved an estimated 18 to 27 million hectares from being brought into agricultural production. *Proceedings of the National Academy of Sciences*, *110*(21), 8363–8368.

Szerman, D., Assunção, J., Lipscomb, M., & Mobarak, A. M. (2022). Agricultural productivity and deforestation: Evidence from brazil.

Tilman, D. (1998). The greening of the green revolution. *Nature*, *396*(6708), 211–212.

Xu, J., Gao, J., de Holanda, H. V., Rodríguez, L. F., Caixeta-Filho, J. V., Zhong, R., ... Lin, T. (2021). Double Cropping and Cropland Expansion Boost Grain Production in Brazil. *Nature Food*, *2*(4), 264-273.

# Technological Progress and Climate Change: Evidence from the Agricultural Sector

*Daniel Da Mata, Thiago Lobo and Mario Dotta*

## Appendix A Tables and Figures

We present below tables and figures with summary statistics, main coefficients, and robustness results. We begin showing Table A.1 with summary statistics for all dependent and explanatory variables reported in Section 5. We proceed in displaying Tables A.2 and A.3 with $\beta$ coefficients given in Figures 4a through 9.

After, we display figures holding robustness results described in Section 5.7. First, in interest of full disclosure, we show results without controls in Figure A.1. Second, we run Equation (1) for all Brazilian municipalities, including localities from states RS, SC, and PR. The outcomes are shown in Figure A.2. Third, we also test Equation (1) using its elasticity *log-log* version. Results are displayed in Figure (A.3).

We then check outcomes from two different specifications using the concepts of Minimum Comparable Areas (MCAs) and local labor markets (micro-regions). The former are geographic locations assembled by IBGE to account for municipalities' detachments and splits over the last decades. The latter comprise larger geographical areas which include approximately 10 municipalities each—essentially, it represents a local market for labor, goods and services. Figures A.4 and A.5 show the results.

Finally, we show that our results are not affected by the period of booming prices for commodities nor agricultural suitability. Results can be found in Figure A.6.

In summary, our results remain largely valid under such different specifications and approaches.

Table A.1: Summary Statistics

| Statistic | Unit | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Soy Planted Area | hectares | 111,260 | 3,996.4 | 19,143.5 | 0 | 635,000 |
| Soy Quantity Produced | tons | 111,260 | 11,126.0 | 57,212.5 | 0 | 2,157,600 |
| Complementary Crops Areas | hectares | 111,260 | 8,572.8 | 28,826.8 | 0 | 1,167,940 |
| Pastureland | hectares | 111,398 | 29,967.7 | 64,183.8 | 0.0 | 1,648,973.0 |
| Agriculture Area | hectares | 111,260 | 38,577.5 | 74,191.4 | 0.0 | 1,652,607.0 |
| Natural Forest Area | hectares | 111,316 | 96,245.1 | 508,945.7 | 0.0 | 15,512,178.0 |
| Soy Productivity | tons/hectare | 111,400 | 0.8 | 1.3 | 0.0 | 12.0 |
| Complementary Crops Productivity | tons/hectare | 111,400 | 12.5 | 20.3 | 0.0 | 151.3 |
| Beef Cattle Productivity | tons/hectare | 111,400 | 2.2 | 60.6 | 0.0 | 7,947.3 |
| Agriculture Productivity | tons/hectare | 111,400 | 4.9 | 12.1 | 0.0 | 221.1 |
| Soy GHG Emissions | tons of CO2eq. | 100,242 | 1,123.2 | 5,714.6 | 0.0 | 198,464.2 |
| Complementary Crops GHG Emissions | tons of CO2eq. | 100,242 | 5,302.5 | 24,578.8 | 0.0 | 789,586.4 |
| Beef Cattle GHG Emissions | tons of CO2eq. | 100,242 | 61,800.7 | 153,359.0 | 0.0 | 4,139,112.0 |
| Agriculture GHG Emissions | tons of CO2eq. | 100,242 | 67,103.2 | 159,830.4 | 0.0 | 4,142,229.0 |
| Agric. Efficiency GHG Emissions | tons of CO2eq. | 99,429 | 135,423.6 | 410,231.6 | 0.0 | 12,718,999.0 |
| Gross GHG Emissions | tons of CO2eq. | 111,316 | 314,704.5 | 1,299,030.0 | 0.0 | 100,047,782.0 |
| Average Rain | milimeters | 110,600 | 1,393.4 | 511.5 | 141.7 | 4,043.5 |
| Average Temperature | degrees Celsius | 110,600 | 22.9 | 3.1 | 13.3 | 31.0 |
| Latitude | degrees | 111,400 | −16.5 | 8.3 | −33.7 | 4.7 |
| Longitude | degrees | 111,400 | −46.2 | 6.4 | −73.4 | −32.4 |
| 1991 Poverty Rate | percentage | 110,800 | 31.0 | 20.9 | 0.1 | 92.7 |
| 1991 Illiteracy Rate | percentage | 110,920 | 31.1 | 16.9 | 1.8 | 88.4 |
| 1991 Population | count | 110,920 | 26,408.5 | 168,334.9 | 555 | 9,652,391 |
| GE Soy Differential | design | 111,400 | −0.0 | 1.0 | −7.0 | 2.0 |
| Cotton Differential | design | 111,400 | −0.0 | 1.0 | −7.0 | 2.0 |
| Maize Differential | design | 111,400 | −0.0 | 1.0 | −7.0 | 2.0 |

*Notes.* This table presents the descriptive statistics of all relevant variables taken into account in the estimations performed in this paper. The analysis period is from 2001 to 2017.

# Table A.2: Main coefficients for Area and Productivity

| | Area/Quantity | | | | | | | | | | | | Productivity | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Soy Planted | | Soy Quantity | | Temp. Crops | | Pasture | | Agriculture | | Natural Forest | | Soy | | Temp. Crops | | Beef Cattle | | Agriculture | |
| **Year** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** |
| **1998** | -32.053 | 0.421 | -461.955 | 0.000 | -43.201 | 0.450 | -192.953 | 0.055 | -234.516 | 0.044 | 245.343 | 0.022 | -0.025 | 0.000 | 0.053 | 0.615 | -0.035 | 0.841 | 0.158 | 0.000 |
| **1999** | -53.027 | 0.149 | -214.993 | 0.036 | -37.598 | 0.504 | -196.433 | 0.019 | -232.180 | 0.014 | 368.281 | 0.000 | -0.008 | 0.028 | -0.035 | 0.703 | -0.046 | 0.795 | 0.045 | 0.247 |
| **2000** | -57.006 | 0.085 | -134.685 | 0.194 | -98.951 | 0.045 | -6.499 | 0.900 | -106.161 | 0.127 | 146.684 | 0.006 | -0.019 | 0.000 | -0.013 | 0.892 | 0.160 | 0.265 | -0.007 | 0.853 |
| **2002** | 199.421 | 0.000 | 570.656 | 0.000 | 151.911 | 0.006 | 5.147 | 0.947 | 160.435 | 0.073 | -204.104 | 0.007 | 0.020 | 0.000 | -0.034 | 0.776 | 0.039 | 0.903 | 0.044 | 0.251 |
| **2003** | 374.066 | 0.000 | 1122.845 | 0.000 | 346.454 | 0.000 | -32.090 | 0.775 | 318.271 | 0.011 | -114.126 | 0.267 | 0.040 | 0.000 | 0.311 | 0.009 | -0.190 | 0.175 | 0.205 | 0.000 |
| **2004** | 653.416 | 0.000 | 1221.780 | 0.000 | 710.031 | 0.000 | -330.531 | 0.027 | 384.710 | 0.022 | -82.607 | 0.565 | 0.045 | 0.000 | 0.407 | 0.000 | 0.095 | 0.765 | 0.293 | 0.000 |
| **2005** | 767.898 | 0.000 | 1822.428 | 0.000 | 850.035 | 0.000 | -605.143 | 0.001 | 250.547 | 0.225 | -82.360 | 0.649 | 0.054 | 0.000 | 0.435 | 0.001 | 0.104 | 0.738 | 0.305 | 0.000 |
| **2006** | 713.095 | 0.000 | 1365.064 | 0.000 | 755.678 | 0.000 | -705.370 | 0.001 | 56.777 | 0.802 | -65.080 | 0.759 | 0.044 | 0.000 | 0.655 | 0.000 | 0.635 | 0.390 | 0.356 | 0.000 |
| **2007** | 524.688 | 0.000 | 1676.871 | 0.000 | 820.025 | 0.000 | -853.073 | 0.000 | -24.668 | 0.924 | -121.090 | 0.618 | 0.068 | 0.000 | 1.279 | 0.000 | 1.316 | 0.368 | 0.611 | 0.000 |
| **2008** | 571.813 | 0.000 | 2012.777 | 0.000 | 1017.648 | 0.000 | -1075.643 | 0.000 | -49.062 | 0.863 | -40.837 | 0.877 | 0.074 | 0.000 | 1.241 | 0.000 | -0.178 | 0.307 | 0.754 | 0.000 |
| **2009** | 602.110 | 0.000 | 1843.095 | 0.000 | 998.249 | 0.000 | -1157.667 | 0.000 | -148.753 | 0.621 | 71.876 | 0.798 | 0.054 | 0.000 | 1.426 | 0.000 | -0.016 | 0.954 | 0.802 | 0.000 |
| **2010** | 705.209 | 0.000 | 2498.722 | 0.000 | 1202.379 | 0.000 | -1278.504 | 0.000 | -65.185 | 0.834 | -123.019 | 0.669 | 0.068 | 0.000 | 1.465 | 0.000 | 0.100 | 0.697 | 0.753 | 0.000 |
| **2011** | 720.433 | 0.000 | 2799.718 | 0.000 | 1363.029 | 0.000 | -1318.994 | 0.000 | 56.018 | 0.859 | -173.487 | 0.551 | 0.077 | 0.000 | 1.801 | 0.000 | 0.208 | 0.558 | 0.902 | 0.000 |
| **2012** | 900.720 | 0.000 | 2854.892 | 0.000 | 1940.299 | 0.000 | -1569.315 | 0.000 | 384.204 | 0.281 | -106.765 | 0.745 | 0.070 | 0.000 | 1.327 | 0.000 | 0.121 | 0.696 | 0.770 | 0.000 |
| **2013** | 1089.835 | 0.000 | 3254.922 | 0.000 | 2159.451 | 0.000 | -1752.463 | 0.000 | 420.166 | 0.250 | -131.234 | 0.682 | 0.091 | 0.000 | 1.574 | 0.000 | -0.059 | 0.730 | 0.924 | 0.000 |
| **2014** | 1132.175 | 0.000 | 3696.985 | 0.000 | 2254.152 | 0.000 | -2050.825 | 0.000 | 218.073 | 0.561 | -55.135 | 0.867 | 0.079 | 0.000 | 1.381 | 0.000 | 1.063 | 0.424 | 0.887 | 0.000 |
| **2015** | 1416.584 | 0.000 | 4380.015 | 0.000 | 2438.637 | 0.000 | -2083.846 | 0.000 | 370.575 | 0.350 | 118.639 | 0.735 | 0.096 | 0.000 | 1.566 | 0.000 | -0.294 | 0.086 | 0.946 | 0.000 |
| **2016** | 1455.854 | 0.000 | 4419.794 | 0.000 | 2594.822 | 0.000 | -2363.890 | 0.000 | 247.103 | 0.550 | 72.759 | 0.844 | 0.113 | 0.000 | 1.806 | 0.000 | 0.698 | 0.371 | 0.908 | 0.000 |
| **2017** | 1549.809 | 0.000 | 5835.747 | 0.000 | 2807.172 | 0.000 | -2528.453 | 0.000 | 294.861 | 0.502 | 211.158 | 0.582 | 0.148 | 0.000 | 1.070 | 0.000 | -0.020 | 0.924 | 0.721 | 0.000 |

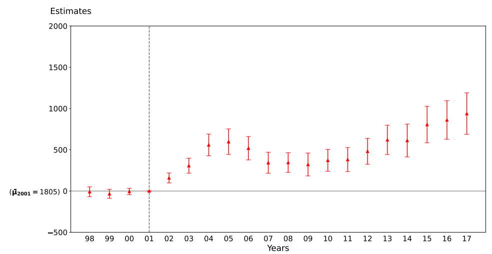
*Notes.* This table presents results from Equation (1) for dependent variables “Soybean Planted Area", “Soybean Quantity", “Complementary Crops Area", “Beef Cattle Pasture Area (Pastureland)", “Agriculture Area", “Natural Forest Area", “Soy Productivity", “Complementary Crops Productivity", “Beef Cattle Productivity", and “Agriculture Productivity". Time period ranges from 1998 to 2017 and base year is 2001. The coefficients above are the same as those presented in Figures 4a, 8, and **??**.

## Table A.3: Main coefficients for GHG Emissions Variables

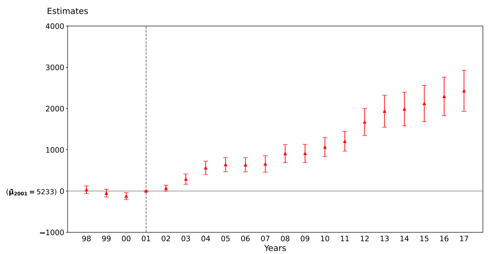
| | GHG Em. - Soybeans | | GHG Em. - Temp. Crops | | GHG Em. - Beef Cattle | | GHG Em. - Agriculture | | Efficiency Em. (Agric.) | | Total GHG Em. | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) | (vii) | (viii) | (ix) | (x) | (xi) | (xii) |
| **Years** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** | $\beta$ | **P-value** |
| **2000** | -25.445 | 0.003 | -24.022 | 0.208 | -437.454 | 0.071 | -461.476 | 0.058 | 3238.163 | 0.002 | 19083.740 | 0.000 |
| **2002** | 68.057 | 0.000 | 53.900 | 0.007 | 212.791 | 0.297 | 266.691 | 0.187 | 647.339 | 0.475 | -12435.431 | 0.183 |
| **2003** | 117.538 | 0.000 | 146.085 | 0.000 | 1215.575 | 0.000 | 1361.660 | 0.000 | 808.555 | 0.527 | -25621.309 | 0.165 |
| **2004** | 126.088 | 0.000 | 191.410 | 0.000 | 1535.209 | 0.002 | 1726.619 | 0.000 | -2453.301 | 0.072 | -18681.301 | 0.120 |
| **2005** | 185.529 | 0.000 | 200.508 | 0.000 | 800.782 | 0.163 | 1001.291 | 0.083 | 211.113 | 0.903 | -40009.852 | 0.003 |
| **2006** | 158.264 | 0.000 | 318.713 | 0.000 | -19.972 | 0.972 | 298.741 | 0.594 | -250.434 | 0.895 | -59147.746 | 0.000 |
| **2007** | 178.422 | 0.000 | 475.573 | 0.000 | -1664.317 | 0.006 | -1188.744 | 0.047 | -5628.001 | 0.013 | -48777.656 | 0.000 |
| **2008** | 222.249 | 0.000 | 644.580 | 0.000 | -1603.889 | 0.012 | -959.308 | 0.129 | -7144.734 | 0.002 | -35627.230 | 0.000 |
| **2009** | 203.112 | 0.000 | 580.802 | 0.000 | -932.864 | 0.182 | -352.063 | 0.612 | -3313.869 | 0.192 | -41314.871 | 0.000 |
| **2010** | 265.663 | 0.000 | 684.884 | 0.000 | -634.567 | 0.413 | 50.316 | 0.948 | -3745.917 | 0.186 | -47625.094 | 0.000 |
| **2011** | 303.274 | 0.000 | 949.091 | 0.000 | -1191.733 | 0.119 | -242.641 | 0.748 | -10724.673 | 0.000 | -43566.297 | 0.000 |
| **2012** | 302.801 | 0.000 | 954.970 | 0.000 | -585.398 | 0.502 | 369.572 | 0.667 | -12078.703 | 0.000 | -33973.262 | 0.001 |
| **2013** | 344.610 | 0.000 | 1087.676 | 0.000 | -950.978 | 0.292 | 136.698 | 0.878 | -10611.971 | 0.001 | -32203.912 | 0.001 |
| **2014** | 385.317 | 0.000 | 1128.804 | 0.000 | -928.459 | 0.299 | 200.346 | 0.820 | -14131.700 | 0.000 | -44704.254 | 0.000 |
| **2015** | 450.976 | 0.000 | 1187.546 | 0.000 | -709.714 | 0.466 | 477.832 | 0.620 | -14248.270 | 0.000 | -54870.574 | 0.000 |
| **2016** | 458.409 | 0.000 | 1140.823 | 0.000 | -368.192 | 0.719 | 772.631 | 0.447 | -23027.889 | 0.000 | -83293.523 | 0.000 |
| **2017** | 559.449 | 0.000 | 1386.843 | 0.000 | -388.446 | 0.705 | 998.396 | 0.329 | -21831.801 | 0.000 | -61691.879 | 0.000 |

*Notes.* This table presents results from Equation (1) for dependent variables “Soybean GHG Emissions", “Complementary Crop GHG Emissions", “Beef Cattle GHG Emissions", “Agriculture GHG Emissions", “Efficiency GHG Emissions", and “Aggregate GHG Emissions". Time period ranges from 2000 to 2017 and base year is 2001. The coefficients above are the same as those presented in Figures 7, 10, and 9.

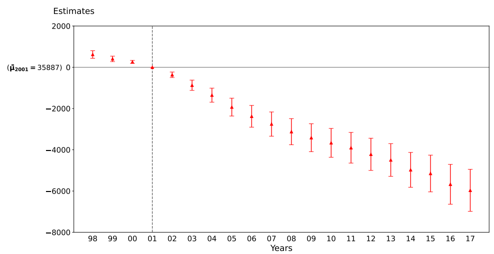
Figure A.1: Robustness Checks—Main Findings without South Region and without Controls



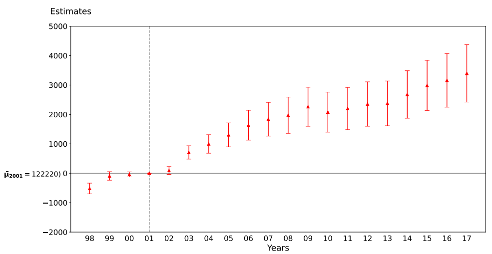

(a) Soybeans Planted Area (hectares)



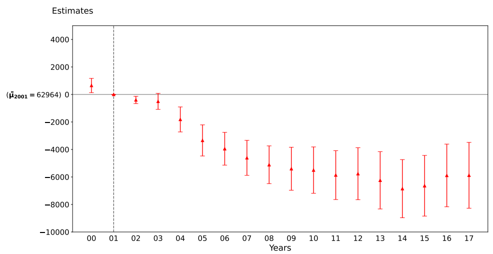

(b) Complementary Crops Area (hectares)



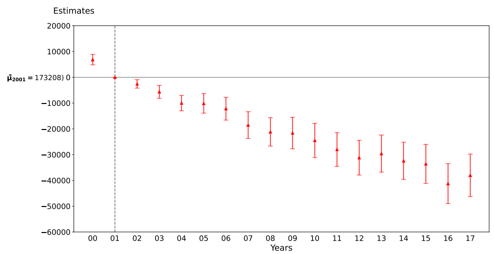

(c) Pastureland (hectares)




(d) Natural Forest Area (in hectares)



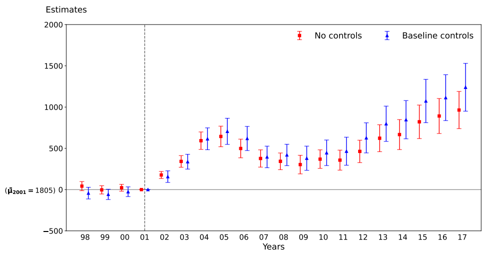

(e) Agriculture GHG Emissions (tons of CO2eq.)



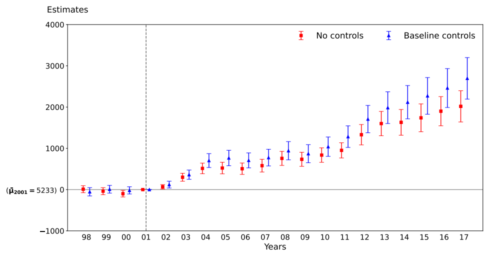

(f) Agriculture GHG Emissions Per Productivity (tons of CO2eq. per tons per hectare)

*Notes:* This figure presents the results of Equation (1) for dependent variables: “Soybeans Planted Area", “Complementary Crops Area", “Pastureland", “Natural Forest Area", “Agriculture GHG Emissions", and “Agriculture GHG Emissions Per Productivity". Panel (a) presents the impacts of soy technology on soybeans area in hectares. Panel (b) shows the impacts of technology exposure on complementary crop area. Panel (c) displays the results on pastureland. Panel (d) shows the effects on natural forest area. Panel (e) presents results of GE soy exposure on agriculture GHG emissions. Panel (f) shows the impacts on efficiency emissions. All results presented do not include baseline controls nor the Southern-region states (RS, SC, and PR). We cluster standard errors at the municipality level.

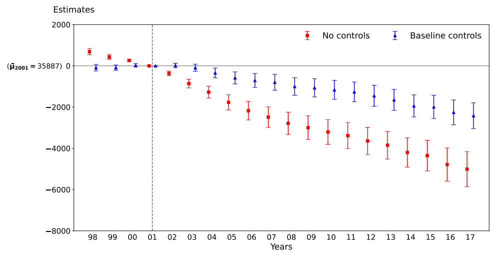
Figure A.2: Robustness Checks—Main Findings for Brazil (with South Region, and with and without Controls)



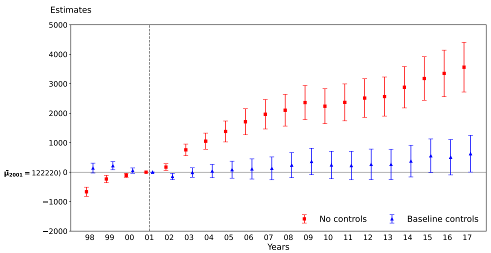

(a) Soybeans Planted Area (hectares)



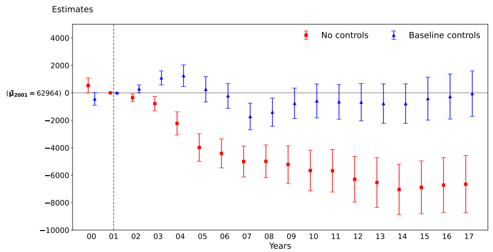

(b) Complementary Crops Area (hectares)



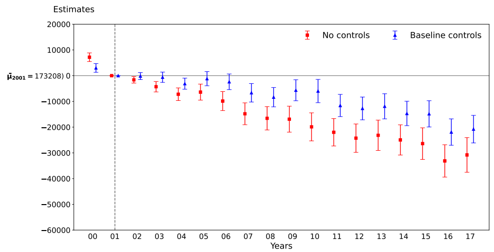

(c) Pastureland (hectares)




(d) Natural Forest Area (in hectares)



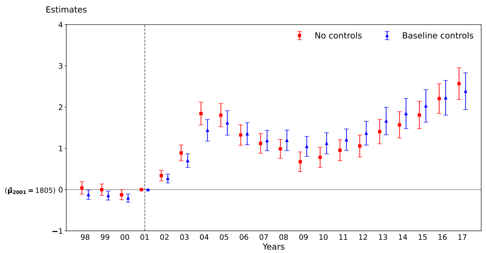

(e) Agriculture GHG Emissions (tons of CO2eq.)



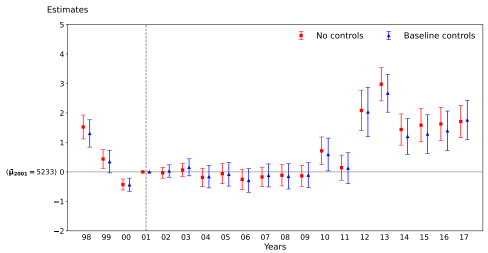

(f) Agriculture GHG Emissions Per Productivity (tons of CO2eq. per tons per hectare)

*Notes:* This figure presents the results of Equation (1) for dependent variables: "Soybeans Planted Area", "Complementary Crops Area", "Pastureland", "Natural Forest Area", "Agriculture GHG Emissions", and "Agriculture GHG Emissions Per Productivity". Panel (a) presents the impacts of soy technology on soybeans area in hectares. Panel (b) shows the impacts of technology exposure on complementary crop area. Panel (c) displays the results on pastureland. Panel (d) shows the effects on natural forest area. Panel (e) presents results of GE soy exposure on agriculture GHG emissions. Panel (f) shows the impacts on efficiency emissions. Results include no controls and baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. All results also include the Southern-region states (RS, SC, and PR). We cluster standard errors at the municipality level.

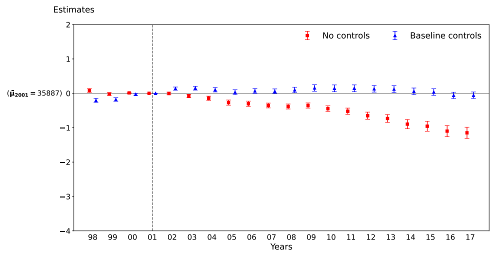
Figure A.3: Robustness Checks—Main Findings with elasticity and without the South Region



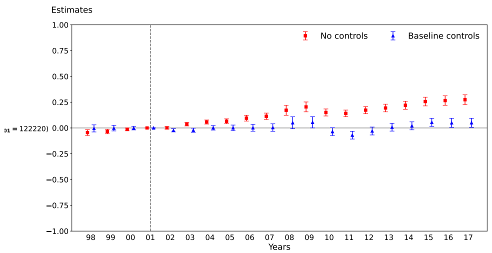

(a) Soybeans Planted Area (hectares)



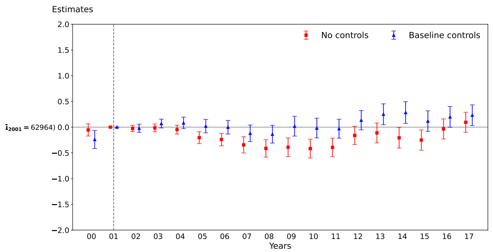

(b) Complementary Crops Area (hectares)



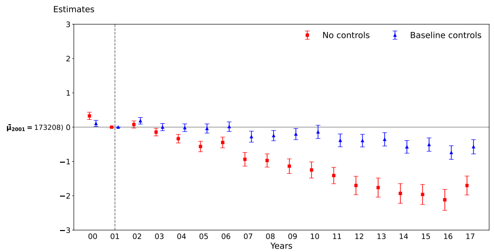

(c) Pastureland (hectares)




(d) Natural Forest Area (in hectares)



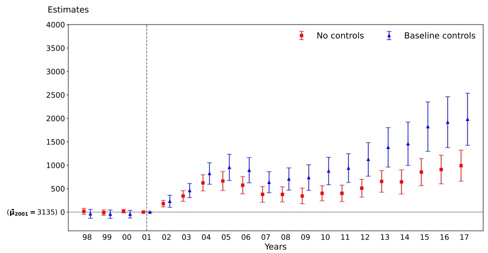

(e) Agriculture GHG Emissions (tons of CO2eq.)



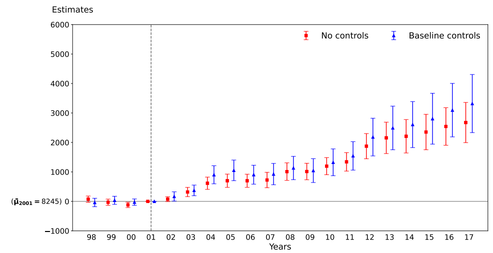

(f) Agriculture GHG Emissions Per Productivity (tons of CO2eq. per tons per hectare)

*Notes:* This figure presents the results of Equation (1) (with *log-log* transformation) for dependent variables: "Soybeans Planted Area", "Complementary Crops Area", "Pastureland", "Natural Forest Area", "Agriculture GHG Emissions", and "Agriculture GHG Emissions Per Productivity". Panel (a) presents the impacts of soy technology on soybeans area in hectares. Panel (b) shows the impacts of technology exposure on complementary crop area. Panel (c) displays the results on pastureland. Panel (d) shows the effects on natural forest area. Panel (e) presents results of GE soy exposure on agriculture GHG emissions. Panel (f) shows the impacts on efficiency emissions. Results include no controls and baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. All results do not include the Southern-region states (RS, SC, and PR). We cluster standard errors at the municipality level.

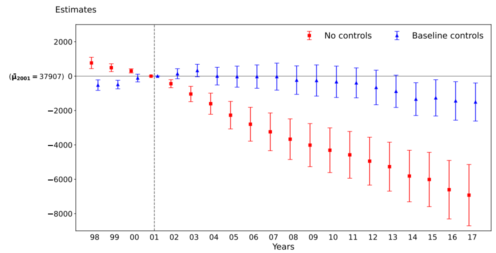
Figure A.4: Robustness Checks—Main Findings with Minimum Comparable Areas (MCAs) and without the South Region



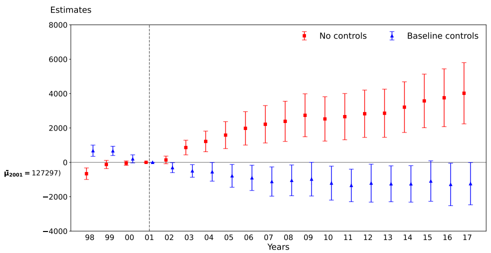

(a) Soybeans Planted Area (hectares)



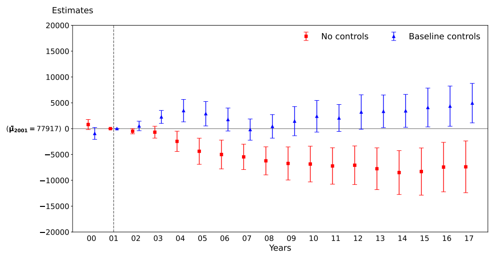

(b) Complementary Crops Area (hectares)



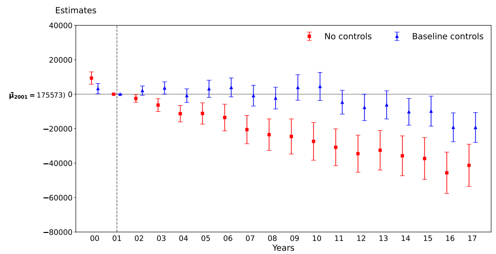

(c) Pastureland (hectares)




(d) Natural Forest Area (in hectares)



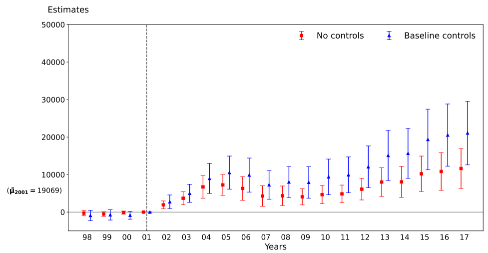

(e) Agriculture GHG Emissions (tons of CO2eq.)



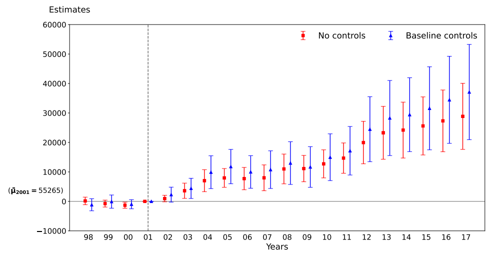

(f) Agriculture GHG Emissions Per Productivity (tons of CO2eq. per tons per hectare)

*Notes:* This figure presents the results of Equation (1) for dependent variables: "Soybeans Planted Area", "Complementary Crops Area", "Pastureland", "Natural Forest Area", "Agriculture GHG Emissions", and "Agriculture GHG Emissions Per Productivity". We consider minimum comparable areas (MCAs) as unit of analysis. Panel (a) presents the impacts of soy technology on soybeans area in hectares. Panel (b) shows the impacts of technology exposure on complementary crop area. Panel (c) displays the results on pastureland. Panel (d) shows the effects on natural forest area. Panel (e) presents results of GE soy exposure on agriculture GHG emissions. Panel (f) shows the impacts on efficiency emissions. Results include no controls and baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. All results do not include the Southern-region states (RS, SC, and PR). We cluster standard errors at the municipality level.

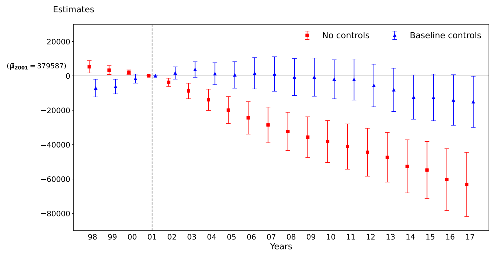
Figure A.5: Robustness Checks—Main Findings with Local Labor Markets (micro-regions) and without the South Region



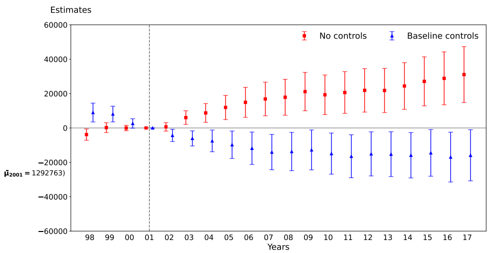

(a) Soybeans Planted Area (hectares)



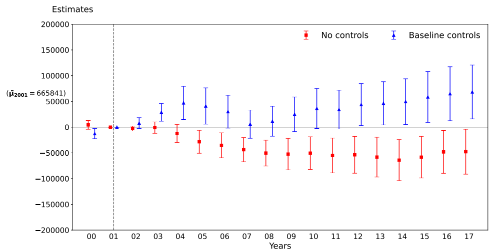

(b) Complementary Crops Area (hectares)



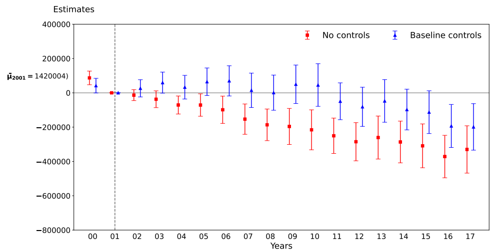

(c) Pastureland (hectares)




(d) Natural Forest Area (in hectares)



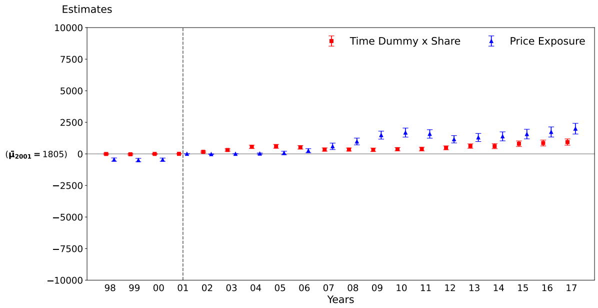

(e) Agriculture GHG Emissions (tons of CO2eq.)



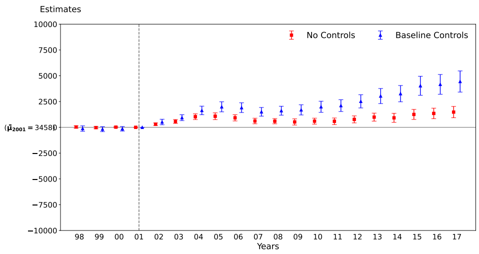

(f) Agriculture GHG Emissions Per Productivity (tons of CO2eq. per tons per hectare)

*Notes:* This figure presents the results of Equation (1) for dependent variables: "Soybeans Planted Area", "Complementary Crops Area", "Pastureland", "Natural Forest Area", "Agriculture GHG Emissions", and "Agriculture GHG Emissions Per Productivity". We consider IBGE's definition of micro-regions as units of analysis (total of 510 units). Panel (a) presents the impacts of soy technology on soybeans area in hectares. Panel (b) shows the impacts of technology exposure on complementary crop area. Panel (c) displays the results on pastureland. Panel (d) shows the effects on natural forest area. Panel (e) presents results of GE soy exposure on agriculture GHG emissions. Panel (f) shows the impacts on efficiency emissions. Results include no controls and baseline controls: pre-period poverty and illiteracy rates, pre-period population, average rain, average temperature, latitude and longitude, and technology controls for maize and cotton. All results do not include the Southern-region states (RS, SC, and PR). We cluster standard errors at the municipality level.

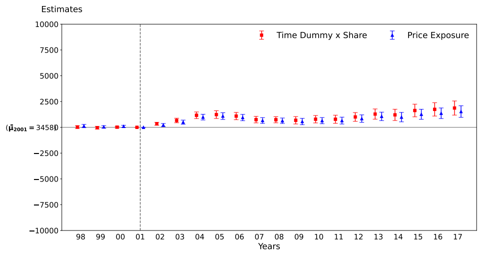
Figure A.6: Robustness Checks—Drivers of Soy Planted Area



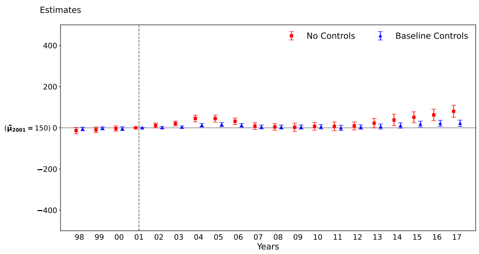

(a) Time Dummy and Commodity Exposure Controls



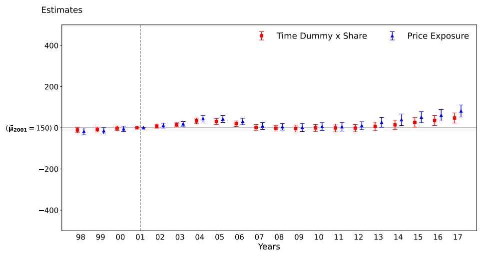

(b) Above Median (baseline)




(c) Above Median (commodity controls)




(d) Below Median (baseline)




(e) Below Median (commodity controls)

*Notes:* This figure presents the results for Equation (1) for dependent variable: "Soybeans Planted Area". All Panels use Da Mata and Dotta (2022) commodity exposure measure (prices and agricultural suitability). Panel (a) displays our main specification controlling for agricultural suitability interacted with time dummy (Time Dummy x Share) and price exposure. Panels (b) and (c) subsets the data into above median and displays our main results (with and without control) and the alternative set of controls (agricultural suitability and price exposure). Panel (d) and (e) displays the same analysis for the below average subset. All results include municipality and time fixed effects and exclude the Southern-region states (RS, SC, and PR). We cluster standard errors at the municipality level.