How corn reshapes fuel consumption, emissions, and the labor market in Brazil?

Laís Soares[*] Leonardo Cardoso[†] Graziella Magalhães[‡]

Abstract

This paper examines the local impacts of corn ethanol adoption in Brazil on fuel consumption, CO_2 emissions, and labor market outcomes. Using a municipality-level panel dataset from 2010 to 2023, we distinguish between two production technologies: full plants, which process corn exclusively, and flex plants, which process corn during the sugarcane off-season. Employing a differences-in-differences approach, we find that full plants increase ethanol consumption and employment, particularly in the service sector, while flex plants reduce emissions and increase rural employment. These results contribute to the debate on the role of corn ethanol in decarbonization and biofuel-driven development in emerging economies.

Keywords: Corn Ethanol, Energy Consumption, Labor Market Outcomes.
JEL Classification: Q42, Q53, J21.

Resumo

Este artigo examina os impactos locais da adoção do etanol de milho no Brasil sobre o consumo de combustíveis, as emissões de CO_2 e os resultados no mercado de trabalho. Utiliza-se um painel de dados em nível municipal referente ao período de 2010 a 2023, com distinção entre duas tecnologias de produção: usinas full (que processam exclusivamente milho) e usinas flex (que processam milho durante a entressafra da cana-de-açúcar). Por meio de uma abordagem de diferenças-em-diferenças, verifica-se que as usinas full aumentam o consumo de etanol e o emprego, especialmente no setor de serviços, enquanto as usinas flex reduzem as emissões e elevam o emprego rural. Os resultados contribuem para o debate sobre o papel do etanol de milho na descarbonização e no desenvolvimento impulsionado por biocombustíveis em economias emergentes.

Palavras-chave: Etanol de Milho, Consumo de Energia, Mercado de Trabalho.
Classificação JEL: Q42, Q53, J21.

1 Introduction

From the Kyoto Protocol (COP3, 1997) to the recent conference in Belém (COP30, 2025), nations have committed to reducing CO_2 emissions to mitigate the impacts of climate change. The two most widely discussed strategies for decarbonizing developing nations are reducing fossil fuel consumption and combating deforestation. In Brazil, deforestation rates have shown a consistent upward trend since 2013, with a notable 34% increase in forest clearance observed from 2019 to 2020 (Silva-Junior et al., 2021). On the other hand, the country stands out positively in terms of its low intensity of fossil fuel consumption. In 2022, fossil fuels accounted for 84% of global primary energy but only 48% in Brazil (Ritchie et al., 2022). It is attributed to the widespread adoption of biofuels in transportation and the contribution of hydropower plants to the country's electricity generation in the country.

---

[*] Department of Rural Economics (DER), Postgraduate Program in Applied Economics (PPGEA), Federal University of Viçosa (UFV). Corresponding author at lais.abreu@ufv.br.

[†] PPGEA, UFV, leonardocardoso@ufv.br.

[‡] Department of Economics, Federal University of Juiz de Fora, graziella.magalhaes@ufjf.br.

Regarding biofuels in transportation, the rise of corn-based ethanol is reshaping Brazil's renewable energy sector. Since the country began producing ethanol from corn in 2018 (see Figure 1 for the evolution of ethanol production by feedstock), corn has rapidly gained ground and accounted for 17% of total ethanol output by 2024 – a scenario that seemed unlikely in the early 2010s (Unicadata, 2023). Despite this growth, the broader implications of corn ethanol in Brazil remain little explored. This paper addresses this gap by examining the effects of corn ethanol adoption on fuel consumption, emissions, and rural labor markets in the most affected regions. Specifically, it aims to: (i) assess the likelihood of sugarcane mills incorporating corn as a complementary feedstock; (ii) estimate the probability of cities hosting corn ethanol plants; (iii) evaluate the impact of the technology on ethanol consumption and CO_2 emissions; and (iv) analyze its effects on employment and local labor market dynamics.

Brazil has implemented two major biofuel initiatives: ethanol and biodiesel. Ethanol emerged as a gasoline substitute following the launch of the Pro-Alcohol Program, established during the 1970s oil crisis to reduce the country's dependence on imported gasoline (Wilkinson and Herrera, 2010). This reduction has been achieved by anhydrous ethanol, which is blended with gasoline and hydrated ethanol that serves as a standalone fuel. In Brazil, fuel stations do not sell pure gasoline – all light vehicles (cars and motorcycles) necessarily run on biofuel blends: either the mandatory E27 (regular gasoline), E25 (premium gasoline), or the optional E100 (hydrated ethanol)[1]. Because the blending of anhydrous ethanol is mandated by law, its effects are uniformly distributed nationwide. In contrast, the use of hydrated ethanol (E100) is voluntary and strongly influenced by relative prices and the proximity to ethanol distilleries. These distilleries are typically located near sugarcane plantations, as sugarcane is the primary feedstock for ethanol production in Brazil. Sugarcane cultivation is concentrated in the central-southern states (see Figure 2), with just three states accounting for 75% of total output: São Paulo (52%), Goiás (12%), and Minas Gerais (11%), based on data from the 2022–2023 harvest (Conab, 2023a).

Freitas and Kaneko (2011a) analyze regional ethanol demand in Brazil and find that consumption patterns are not driven by local levels of economic development, but rather by relative prices – strongly influenced by proximity to sugarcane-producing areas. This spatial dependence causes ethanol's competitiveness relative to gasoline to vary considerably across regions. It is evident in both fuel consumption and pricing patterns. Existing research (Pacini and Silveira (2011a); Orellano et al. (2013)) and the widely adopted 70% price-ratio rule posit ethanol as the optimal choice when priced at or below 70% of gasoline. An analysis of ANP (2025) data between 2010 and 2023 at the gas station-week level shows that 32% of observations met the ethanol-viability threshold. However, there are significant regional disparities: while in São Paulo, 60% of observations indicated ethanol as a viable option, in Roraima, Piauí, and Acre, this criterion was met in less than 1% of observations.

The growing presence of corn ethanol in the country may be reshaping regional patterns of fuel consumption. Several factors are driving the emergence of corn ethanol in Brazil. Firstly, corn production and productivity have experienced significant expansion in the last two decades (see Figure 3). Production increased from 58 billion tons in the 2010/2011 harvest to 87 billion tons in the 2020/2021 harvest, while productivity rose from 57 million tons across 13 million hectares (2010/2011 harvest) to 100 million tons across 17 million hectares (2018/2019 harvest)(Conab, 2023b). This surge in production, coupled with the inefficiency of domestic corn transport in Brazil and the distance of production from export ports, has enabled producers of corn-based ethanol in states such as Mato Grosso, Mato Grosso do Sul, and Goiás to access raw materials at advantageous prices[2]. Moreover, the use of precarious roads for transportation in-

---

[1] As of 2025, Brazil requires a 27% anhydrous ethanol blend in regular gasoline (E27) and 25% in premium gasoline (E25), per National Energy Policy Council (CNPE) regulations established under Law No. 8,723/1993.

[2] For instance, Mato Grosso, Brazil's largest corn producer, is approximately a thousand kilometers from export ports.

creases logistical costs and creates opportunities for utilizing products closer to production sites, such as through local ethanol processing(Eckert et al., 2018).

The state with the largest corn production, Mato Grosso, was responsible for 33 billion tons produced in the 2020/2021 harvest, and its production more than quadrupled during the period (Conab, 2023b). Between the 2010/2011 and the 2020/2021 harvests, total ethanol production in Brazil increased by 18%, while in Mato Grosso, total ethanol production increased by 288% (Unicadata, 2024). The significant increase in corn production in Brazil and the introduction of technology that uses this raw material for biofuel production may introduce a new factor to the competitiveness of Brazilian ethanol: proximity to large corn production areas. One of the advantages of this new production chain is its ability to provide ethanol to regions where its price was previously uncompetitive when compared to gasoline, thus increasing overall consumption.

Secondly, the emergence of flexible refineries capable of producing ethanol from sugarcane and corn has enabled uninterrupted industrial operation. Most sugarcane mills do not operate for a third of the year as sugarcane cannot be stored and has only one harvest a year. According to Neves (2021), adopting the flex model allows these companies to process corn during the idle period, increasing production capacity and contributing to the dilution of the company's fixed costs. Lastly, ethanol production from maize generates co-products with important economic potential, such as Dried Distillers Grains with Soluble (DDGs), used in animal feeding, and vegetable oil (Neves, 2021).

These factors have led to a situation where regions characterized by intensive corn and livestock production are more likely to host corn ethanol plants. It presents challenges in accurately measuring the impacts of corn expansion. Therefore, our empirical strategy comprises two key components. Firstly, we quantify the probability of a city hosting a new corn ethanol facility with a propensity score matching approach. The propensity scores estimated will be used to weight units, and these weights will then be applied in the subsequent comparative analysis of crucial outcomes (such as emissions, fuel consumption, and labor outcomes) employing a Differences-in-Differences (DiD) research design.

Numerous studies have examined the price dynamics (Cavalcanti et al., 2012; El Montasser et al., 2015; Kristoufek et al., 2015; Laurini, 2017) and demand (de Andrade Junior et al., 2019; Freitas and Kaneko, 2011b; Orellano et al., 2013; Pacini and Silveira, 2011b) for ethanol from sugarcane in Brazil. Regarding corn ethanol, previous studies, such as those conducted by Eckert et al. (2018) and Silva and Castañeda-Ayarza (2021), have primarily focused on delineating the characteristics, opportunities, and challenges associated with its production. Eckert et al. (2018) elucidates the factors contributing to the emergence of corn ethanol in Brazil and outlines the key differences in the ethanol production process between starchy and saccharide materials. On the other hand, Silva and Castañeda-Ayarza (2021) identifies the political and legal segments as the primary threats to the development of Brazilian corn ethanol, while highlighting the economic sector's abundant opportunities. In contrast, our contribution to this emerging literature lies in providing credible empirical evidence of the consequences of corn ethanol expansion in Brazil within an ex-post scenario, where the initial impacts of corn expansion are already evident. The impact analysis to be conducted in the current paper aims to provide a deeper understanding of these changes and to propose how they can positively impact Brazil's energy matrix.

2 Background and Context

2.1 Corn Ethanol in Brazil

Ethanol is derived from three distinct types of raw materials: saccharide-based products, known for their sucrose sugar composition; amylaceous-based products, characterized by their starch content; and cellulose-based products, primarily composed of cellulose. While sugarcane falls into the saccharide-based category, corn is classified as an amylaceous-based raw material. Consequently, significant disparities exist in the production processes for sugarcane ethanol and corn ethanol. In the case of saccharide-based products, the production process entails the extraction of sucrose through either pressing or diffusion, resulting in a must. This is followed by fermentation, ultimately leading to distillation, yielding ethanol (Neves, 2021). For amylaceous-based products, sugars are not readily accessible within the biomass. In such instances, enzymatic hydrolysis becomes essential following a milling phase, but prior to the fermentation stage. This intricate process involves an enzyme-catalyzed reaction responsible for breaking down starch into fermentable sugar molecules. Another notable contrast in production is the utilization of biomass for energy generation. Sugarcane processing mills employ the biomass of the raw material, known as bagasse, for energy production within the process. In contrast, corn processing mills rely on external sources for co-generating energy (Bothast and Schlicher, 2005).

Corn can be cultivated in three distinct seasons in Brazil. When harvested during the summer, it is referred to as the first corn crop. Sowing from January onward defines the second crop, while planting between May and June marks the third crop. In the central region – home to the country's largest producers – a production system combining soybeans as the first crop and corn as the second has become increasingly dominant. As shown in Figure 3, the growth in national corn output is largely driven by the expansion of second-crop production (Neves, 2021).

The predominant use of second-crop corn for ethanol production in Brazil contrasts sharply with the United States, where ethanol is produced almost exclusively from first-crop corn. This crop rotation strategy, typically involving soybeans followed by corn, not only reduces competition with food production but also lessens land-use pressure, addressing key concerns in the food-versus-fuel debate (Moreira et al., 2020). Another major distinction lies in the energy source used in ethanol processing: while U.S. facilities largely depend on fossil fuels, Brazilian plants rely primarily on eucalyptus biomass, making the process less carbon-intensive (Moreira et al., 2020).

Corn ethanol production also has the advantage of generating the by-product Distillers Dried Grains with Soluble (DDGs). For each ton of corn used in ethanol production, 323 kg of DDGS are produced (Silva and Castañeda-Ayarza, 2021). This co-product presents significant potential as an alternative feed, capable of substituting corn and soybean in animal nutrition (Silva and Castañeda-Ayarza, 2021) and enhancing efficiency and productivity indicators for meat production.

As cited by Neves (2021), the primary costs of corn ethanol production are associated with raw materials, followed by biomass used in energy co-generation and inputs utilized in the industrial process, such as hydrolysis enzymes. The author underscores that, in light of the price volatility of the product, strategies such as price hedging, pre-purchasing of grains, storage, and, most importantly, leveraging supplementary revenues from by-products like DDGs, oil, and energy, become indispensable. In a full-scale plant, as detailed in the following subsection, the revenue composition typically comprises 83% ethanol, 13% DDGs, 2% vegetable oil, 1% surplus energy co-generated in the industrial process, and 1% other products (Neves, 2021).

2.2 Comparative Impacts of Flex and Full Distilleries

In Brazil, three types of distilleries produce ethanol from corn: the *full*, the *flex* and the *flex fuel* mills. The *full* mill uses corn exclusively as its raw material. The *flex* mill employs corn for ethanol production only during the idle periods of sugarcane harvests. Finally, the *flex fuel* mill processes both corn and sugarcane throughout the year, rather than limiting production to the idle periods of sugarcane harvesting.

Flex and *flex fuel* mills, hereafter in this section simply referred to as *flex* mills, led the way in corn-based ethanol production within the country. They efficiently utilize a significant portion of the existing sugarcane processing infrastructure, requiring only the addition of adjacent facilities. Consequently, the necessary investment is notably lower compared to *full* mills. Moreover, they tap into the available energy potential in the surplus bagasse (Neves, 2021). These two types of mills provide the opportunity for enhanced ethanol production in regions already established as producers (Moreira et al., 2020).

The sugarcane-based mills operate only during the harvest season (April to November), decreasing significantly their production during the off-season, leading to increased reliance on imports, primarily from the United States, which exerts upward pressure on domestic prices. This raises a critical question: why does Brazil import biofuels during the sugarcane off-season? The explanation lies in the country's fixed blending mandate: because the anhydrous ethanol-gasoline mixing ratio does not adjust seasonally, fuel distributors are compelled to import ethanol to meet regulatory requirements.

By adopting corn as a raw material to be processed alongside sugarcane in *flex* mills, distilleries can sustain year-round operations, rather than being restricted to the sugarcane harvest period. This flexibility is essential for optimizing the use of milling facilities and ensuring consistent production throughout the entire year. As stated by Neves (2021), *flex* mills typically operate for 330 to 350 days annually. In this context, integrating corn ethanol technology, as highlighted by Silva and Castañeda-Ayarza (2021), serves as an effective strategy for reducing operational downtime and dilute operational costs.

Conversely, *full* mills are most common in regions with significant corn production (see Figuere 4), mainly in the Center-South states. They mirror the facilities found in the world's largest ethanol producer, the United States, which focuses exclusively on corn processing. Unlike sugarcane ethanol, which is restricted to specific regions due to high transportation costs, perishability, and limited storability, *full* mills allow for biofuel production in previously untapped areas. In this context, while adopting the *flex* model increases the relative use of ethanol by maintaining its competitiveness year-round, the adoption of *full* mills boosts biofuel competitiveness in regions where ethanol use was previously negligible.

When assessing the socioeconomic and environmental impacts of corn-based ethanol, several key factors must be considered, as the flex and full production models involve distinct processes. From an environmental perspective, the utilization of sugarcane ethanol as a substitute for gasoline has been favorably assessed regarding its CO_2 emissions in studies pertaining to the subject (De Oliveira and Coelho, 2017; Goldemberg et al., 2008; Walter et al., 2014). According to De Oliveira and Coelho (2017) and Anderson (2009), the positive impacts of reduced CO_2 emissions from the use of sugarcane ethanol are particularly noticeable in air quality improvement and attributed partly to the fact that the production process does not require the use of fossil fuels. However, as cited by De Oliveira and Coelho (2017) there are possible negative impacts associated with the expansion of sugarcane cultivation areas for ethanol production, including deforestation, soil degradation, contamination of water resources, and the substitution of food crops with sugarcane intended for ethanol production.

For corn ethanol, different scenarios exist regarding the *flex* production model and the *full* production model. In the *flex* process, the production requires smaller volumes of corn, but the transportation distances for the feedstock are usually longer than in the *full* process. Another important factor is the energy used within the production process: while most *flex* mills can use the energy provided by sugarcane biomass (bagasse), *full* mills rely on external sources for co-generating energy, typically sourced from eucalyptus biomass. While the use of eucalyptus for energy generation reduces emissions compared to scenarios where fossil fuels are used, as is the case of corn ethanol production in US, it is still less environmentally advantageous than the scenario involving *flex* and sugarcane-specialized mills.

The adoption of both *flex* and *full* production models is expected to increase ethanol consumption and, consequently, reduce CO_2 emissions. However, the sustainability of this shift hinges on controlling emissions generated during the production process. A key metric in this regard is the energy balance—the ratio of clean energy produced to fossil energy consumed – which varies depending on the feedstock and production conditions (Silva and Castañeda-Ayarza, 2021).

Note that our paper aims to evaluate the impact of the *flex* and *full* mills on local emissions, rather than assess the energy balance of corn ethanol. Therefore, for *flex* mills, a positive local environmental impact would mean that the emissions reduced through the use of clean energy are greater than the emissions increased during the processing and distribution phases of the biofuel, since feedstock production is usually not local. For *full* mills, where proximity to corn production is essential, a positive local environmental impact would indicate that the emissions reduced by using clean energy are greater than the emissions increased during feedstock production, processing, and distribution.

In socioeconomic terms, as outlined by Silva and Castañeda-Ayarza (2021), corn ethanol production is expected to stimulate employment and income in the regions where it is concentrated. *Full* plants, in particular, rely heavily on labor-intensive inputs – such as maize as the primary feedstock and eucalyptus for energy cogeneration – thereby promoting rural employment, typically the most affected by mechanization. These facilities demand significant labor for the cultivation, harvesting, and processing stages, making the rural workforce a critical component of their operation (Silva and Castañeda-Ayarza, 2021). According to Silva and Castañeda-Ayarza (2021), maize cultivation accounts for approximately 44.5% of the additional jobs generated by corn ethanol production, while eucalyptus cultivation contributes around 7%. However, the substitution of corn and soybeans with DDGs in animal feed may enhance productivity in the cattle sector but could also lead to a decline in rural employment due to the reduced demand for labor in livestock management. Industrial employment also tends to grow to support the processing and refining stages, which generally require more skilled labor. Additionally, the transportation sector benefits from increased job opportunities, as these plants rely on the road transport of large volumes of inputs and final products (Silva and Castañeda-Ayarza, 2021).

Regarding *flex* plants, year-round industrial activity helps sustain jobs that were previously unnecessary during the idle periods between sugarcane harvests (Neves, 2021). In the transportation sector, additional employment is generated through the increased demand for the movement of both inputs and outputs associated with corn ethanol production.

As noted, the establishment of corn ethanol processing plants has significant impacts on labor market dynamics, particularly in the highlighted sectors. However, these effects are not uniform across regions. In areas that host *full* plants, the impacts tend to be more pronounced in rural employment, while in regions with *flex* and *flex-fuel* plants, the effects are generally more significant in the industrial and transportation sectors. This phenomenon will be explored in greater detail later in the paper.

3 Methodology

3.1 Empirical Strategy

This paper examines the local impacts of corn ethanol adoption in Brazil. To do so, we use panel data and employ a doubly robust differences-in-differences approach, proposed by Sant'Anna and Zhao (2020) and Callaway and Sant'Anna (2021). The empirical strategy explores the staggered adoption of two types of treatment, both defined at the municipal level. The first treatment occurs when a municipality i, where there is ethanol production from sugarcane, adopts the flex model (producing the biofuel from sugarcane and corn) in period t. The second type of treatment occurs when a municipality s, where ethanol is not produced, undergoes the implementation of a full corn-producing mill in period t.

Thus, for the first treatment, the treatment group comprises municipalities producing sugarcane ethanol that adopted the *flex* or *flex-fuel* production model, while the control group consists of municipalities producing ethanol solely from sugarcane. For the second treatment, the treatment group comprises municipalities that adopted the *full* model of production, while the control group comprises municipalities that do not produce ethanol.

The canonical Differences-in-Differences (DiD) involves two periods and two groups: a treatment group that receives the intervention in the second period, and a control group that does not receive the treatment in either period. The main parameter of interest in the conventional DiD model is the Average Treatment Effect on the Treated (ATT), which measures that average causal effect on treated units in the period they were treated (Roth et al., 2023).

Two key assumptions are necessary for the identification of the ATT: the parallel trends assumption and the no anticipation assumption. The first assumption posits that, in the absence of treatment, the average outcomes of the treated and control groups would have followed parallel trajectories over time. The second assumption asserts that the treatment has no causal effect on the outcomes prior to its implementation (Roth et al., 2023). However, in practice, not all applications meet the requirements and assumptions of the canonical DiD set up.

In the context of our study, both treatments considered – the adoption of the *flex* model and the adoption of the *full* model of ethanol production – involve multiple periods and units (cities) that are treated at different points in time. Therefore, we adopt the identification strategy proposed by Callaway and Sant'Anna (2021). The model by Callaway and Sant'Anna (2021) generalizes the conventional DiD method, providing a framework to estimate causal effects while allowing for: a) multiple time periods; b) staggered treatment and c) conditional parallel trends.

Unlike the conventional DiD approach, the doubly robust Differences-in-Differences method does not focus on a single parameter, such as the ATT. Instead, it estimates several group-time average treatment effect parameters. These groups are defined by the time at which a unit is first treated, and each specific group-time average treatment effect parameter—denoted as ATT(g,t) – represents the causal effect of the treatment at time t for the group of units first treated at time g. The ATT(g,t) is identified by comparing the expected change in outcome for treatment cohort g between $g-1$ and t to that for a control group of never treated units:

$$ATT(g,t) = E[Y_{i,t} - Y_{i,g-1})|G_i = g] - E[Y_{i,t} - Y_{i,g-1})|G_i = \infty] \tag{1}$$

Where *i* indexes city and *t* denotes year. Y is the outcome variable and G_i is the earliest period at each unit has recieved treatment. In this case, the treatment group is defined by conditioning the value of the adoption date, and the control group is defined as all groups that never adopted treatment, known as the never-treated group.

The estimation of ATT(g,t) relies on the same two key assumptions as the canonical model, but with a relaxed formulation. The anticipation assumption in the reformulation by Callaway and Sant'Anna (2021) is the limited anticipation assumption, which permits anticipation of treatment by treated units, as long as the anticipation horizon is well-defined. This is feasible because the identification of ATT(g, t) parameters allows for the estimation of causal effects in periods prior to the first treatment period for a unit, in other words, when $t < g$.

The parallel trends assumption in Callaway and Sant'Anna (2021) is a conditional generalization, requiring that trends be parallel only after controlling for covariates. This conditional approach adds robustness, particularly when differences in observed characteristics between treatment and control groups may lead to time-varying effects. In such cases, conditional random assignment may fail, introducing endogeneity concerns. To address this, the doubly robust difference-in-differences method constructs a weighted control group based on propensity scores estimated from covariates. This approach combines inverse probability weighting with outcome regression to more credibly estimate treatment effects over time (Sant'Anna and Zhao, 2020).

In the first step, treatment in both cases is assumed to depend on characteristics that can also affect the outcomes of interest regarding their time trend. In this case, a method to mitigate selection bias involves estimating the treatment model, where the treatment indicator is regressed on covariates influencing treatment adoption and outcomes. This regression, typically specified using a $logit$ model, yields the propensity score, representing the likelihood of units receiving treatment. Propensity scores are then used to define regression weights, inversely proportional to treatment probability (Callaway and Sant'Anna, 2021; Sant'Anna and Zhao, 2020).

In the present study, there are two treatments to consider: the adoption of the *full* model of corn ethanol production and the adoption of the *flex* model in sugarcane mills. In both cases, we assume that a set of factors influences the probability of treatment adoption, leading to significant differences between the control and treatment groups and that some of these characteristics may affect the trajectory of the outcomes of interest (relative ethanol consumption, CO_2 emissions and employment).

For both *full* and *flex* corn ethanol plants, we consider four main factors influencing the likelihood of treatment adoption across municipalities, in line with the literature: initial relative ethanol consumption; proximity to corn and livestock production areas (due to input needs and DDG commercialization, respectively); and local economic development (measured by per capita GDP), which reflects both market potential and infrastructure availability (Neves, 2021; Silva and Castañeda-Ayarza, 2021).

Regarding identification, we assume that the parallel trends assumption holds *conditionally* on relevant covariates, depending on the outcome. Specifically, for **relative ethanol consumption**, we condition on initial ethanol consumption and economic development, given their role in shaping fuel demand and sensitivity to supply shocks (Freitas and Kaneko, 2011a). For both CO_2 **emissions** and **employment**, we condition on economic development and proximity to corn and livestock production areas, as these factors are jointly associated with industrial activity, agricultural emissions, and labor market dynamics (Neves, 2021; Silva and Castañeda-Ayarza, 2021).

While the same factors apply to *flex* mills, proximity to corn-producing regions is relatively less critical, as these plants can substitute inputs with sugarcane and thus tolerate longer maize transport distances. Nonetheless, cost considerations still imply that geographic proximity to corn supply remains relevant, albeit to a lesser degree.

3.2 Data Source

The data used in this study includes information on all Brazilian municipalities on a yearly basis, from 2010 to 2023. Information on ethanol and gasoline consumption is obtained from the National Petroleum, Natural Gas, and Biofuels Agency (ANP). ANP provides crucial information regarding ethanol producers in the country, including their localization, production capacity, and the raw materials processed at each distillery. This data on producers is utilized to construct the treatment variables, as it indicates when a distillery adopts the flex model, when a new full mill is implemented, and their respective locations.

Employment data is sourced from the Annual Social Information Report (RAIS), while emissions data is obtained from The Greenhouse Gas Emissions and Removals Estimation System (SEEG). RAIS is a report of socioeconomic information requested annually by the Ministry of Labor and Employment in Brazil with data on the labor market. SEEG provides annual estimates of greenhouse gas emissions in Brazil.

The data on covariates used in the initial phase of the empirical strategy, particularly regarding corn production (in tons) within a 50km radius of a city and livestock size within a 100km radius of a city, are sourced from the Brazilian Institute of Geography and Statistics (IBGE). IBGE conducts the Municipal Agricultural Production (PAM) research annually, which investigates a range of products from both temporary and permanent crops across the country. Similarly, IBGE conducts the Municipal Livestock Research (PPM) annually, which contains information on livestock size, animal production, and production value during the reference year.

4 Results

The second stage of the method proposed by Callaway and Sant'Anna (2021) provides a flexible framework for summarizing the group-time average treatment effects (ATTs) estimated in the first stage. The aggregation can be done in different ways, depending on the research question, for instance:

i) By exposure time (event time): This means grouping observations by the number of periods since they received the treatment, which helps capture dynamic effects – for example, whether the impact of the treatment grows, diminishes, or remains constant over time;

ii) By group-time combinations: This allows identifying heterogeneous effects, meaning that different groups may experience different treatment effects. A particular focus here is to assess whether receiving the treatment earlier has a different impact than receiving it later.

The overall treatment effect is a summary measure that approximates the classical difference-in-differences (DD) average treatment effect on the treated (ATT). It is obtained by first averaging the estimated ATTs across time for each group and then taking the average of these group-level effects. This gives an overall sense of the treatment's impact across all treated units and time periods.

The following two subsections present the results for the two treatments considered in the study. The first subsection shows the overall treatment effect of adopting the *full* model on relative ethanol consumption, emissions, and employment, as well as the event study for each outcome—that is, the dynamic effect plots over time. The next subsection presents the same set of results for the adoption of the *flex* model.

4.1 Impact of *Full* Model Adoption

In 2023, 14 cities had full corn ethanol production plants, with two located in the state of Goiás, nine in Mato Grosso, two in Mato Grosso do Sul, and one in São Paulo. Table 1 below presents the cities, their respective states, and the year in which the treatment was adopted, that is, the year the *full* plants began operating.

Regarding the results, Table 2 presents the overall treatment effect estimates for each variable of interest: relative ethanol consumption, emissions, and employment. It is possible to observe that three variables showed statistically significant coefficients: relative ethanol consumption, overall employment, and employment in the service sector.

The estimated overall treatment effect for relative ethanol consumption is 0.3577. This indicates that, on average, the adoption of *full* corn ethanol plants led to an approximately 35.8 percentage points increase in relative ethanol consumption in treated cities compared to what would have occurred without the treatment. This finding reinforces the potential of this new technology to enhance the competitiveness of the biofuel against fossil fuels in regions where such competitiveness was previously constrained, largely due to the spatial reliance on proximity to sugarcane production.

The estimated overall treatment effect for employment is 0.05 and is statistically significant at the 1% level. This implies that, on average, the adoption of *full* corn ethanol plants resulted in a 5 percentage point increase in employment in the treated cities. This finding suggests that corn ethanol technology has impacts beyond energy production, contributing positively to socioeconomic outcomes as well.

Table 1: Cities with Full Corn Ethanol Plants and Year of Adoption

City	State	Treatment Adoption
Dois Córregos	São Paulo	2016
Sorriso	Mato Grosso	2017
Lucas do Rio Verve	Mato Grosso	2017
Itaúba	Mato Grosso	2018
Chapadão do Céu	Goiás	2019
Sinop	Mato Grosso	2019
Poconé	Mato Grosso	2019
Nova Mutum	Mato Grosso	2020
Nova Marilândia	Mato Grosso	2021
Primavera do Leste	Mato Grosso	2021
Dourados	Mato Grosso do Sul	2022
Acreúna	Goiás	2023
Ipiranga do Norte	Mato Grosso	2023
Maracaju	Mato Grosso do Sul	2023

Source: Authors.

Table 2: Overall Treatment Effect Estimates - Full

Treatment: Adoption of the full model of corn ethanol production	Overall Treatment Effect (ATT)	Std. Error
Relative Ethanol Consumption	0.3577**	0.156
CO_2 Emissions	0.012	0.056
Overall Employment	0.05***	0.013
Rural Employment	0.025	0.073
Industrial Employment	0.259	0.183
Services Employment	0.086***	0.011

Source: Authors.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

When analyzing employment by sector, we observe that the estimated overall treatment effect for employment in the service sector is 0.086, statistically significant at the 1% level. This suggests that, on average, the adoption of *full* corn ethanol plants led to an 8.6 percentage point increase in service sector employment in treated cities. This finding highlights that the expansion of *full* ethanol plants also stimulates job creation in the service sector—likely driven by increased local economic activity and demand for supporting services.

Figure 5 presents the dynamic treatment effects on relative ethanol consumption, emissions, and employment using event study plots. The red lines depict the differences between the treatment and control groups during the pre-intervention periods, while the blue lines illustrate the aggregated treatment effects across groups in the post-intervention periods. The points represent the estimated effects of the event over time relative to the event date.

In Figure 5a, it can be observed that the effect of implementing *full* corn ethanol plants on relative ethanol consumption remains close to zero during the first two years and then becomes positive. This pattern possibly indicates that the effect tends to grow as the production capacity of corn ethanol plants increases. Figure 5b shows that the effect on emissions remains null, which may indicate that the reduction resulting from the substitution of fossil fuels with ethanol is not sufficient to offset the potential increase in emissions caused by their production. Finally, Figure 5c shows that the effect on employment increases during the initial years and then stabilizes, which aligns with the period when the plants ramp up production at the beginning of their operations.

Similar to Figure 5, Figure 6 displays the dynamic treatment effects on employment by sector: rural, industrial, and service. Figure 6a shows that the effect on rural employment is null in the initial years and becomes positive thereafter. This pattern may reflect the limited production capacity during the early stages of plant operation, when corn demand is still insufficient to drive a significant increase in rural labor. It may also indicate that *full* plants tend to be located in areas where corn production is already well established, meaning that their implementation does not substantially alter the local rural labor market.

For industrial employment, the effect is positive in the initial years but fades over time, while for employment in the service sector, the effect remains positive throughout the period.

4.2 Impact of *Flex* Model Adoption

In 2023, 8 cities had *flex* corn ethanol production plants, with four located in the state of Goiás, three in Mato Grosso and one in São Paulo. Table 3 below presents the cities, their respective states, and the year in which the treatment was adopted, that is, the year the *flex* plants began operating.

Table 3: Cities with Flex Corn Ethanol Plants and Year of Adoption

City	**State**	**Treatment Adoption**
Campos de Júlio	Mato Grosso	2012
São José do Rio Claro	São Paulo	2013
Jaciara	Mato Grosso	2014
Rio Verde	Goiás	2015
Quirinópolis	Goiás	2015
Vicentinópolis	Goiás	2018
Santa Helena do Goiás	Goiás	2019
Campo Novo dos Parecis	Mato Grosso	2020

Source: Authors.

Regarding the results, Table 4 presents the overall treatment effect estimates for each variable of interest: relative ethanol consumption, emissions, and employment. It is possible to observe that four variables showed statistically significant coefficients: emissions, overall employment, employment in the rural sector and employment in the industrial sector.

Table 4: Overall Treatment Effect Estimates - Flex

Treatment: Adoption of the flex model of corn ethanol production	**Overall Treatment Effect (ATT)**	**Std. Error**
Relative Ethanol Consumption	0.557	0.678
CO_2 Emissions	-0.047***	0.019
Overall Employment	0.071***	0.014
Rural Employment	0.158***	0.036
Industrial Employment	0.079**	0.036
Services Employment	0.026	0.018

Source: Authors.

The estimated overall treatment effect for emissions is -0.047 and is statistically significant at the 1% level. This suggests that, on average, the adoption of *flex* corn ethanol plants led to a 4.7 percentage point reduction in CO_2 emissions in the treated cities. This outcome indicates that the emission reductions from substituting fossil fuels with ethanol are sufficient to offset the potential increases associated with ethanol production. This result is consistent with the fact that the *flex* process largely relies on the existing infrastructure and energy sources of the sugarcane-based ethanol production, thereby reducing the need for new facilities or additional energy inputs.

The estimated overall treatment effect for employment is 0.071 and is statistically significant at the 1% level. This implies that, on average, the adoption of *flex* corn ethanol plants resulted in a 7 percentage point increase in employment in the treated cities. When analyzing employment by sector, we observe that the estimated overall treatment effect for employment in the rural sector is 0.158 and for industrial employment is 0.079.

This finding highlights that the expansion of *flex* ethanol plants also stimulates job creation in the rural sector, most likely due to the associated growth in corn production. This result was not initially expected and can be explained by the fact that, unlike *full* plants, typically located in regions where corn production is already well established, *flex* plants tend to encourage the development of local maize cultivation. This expansion reduces the need to transport raw materials from other areas, thereby strengthening local supply chains and supporting rural employment. The positive effect on industrial employment aligns with the fact that the adoption of the *flex* model allows for production over a longer period than the sugarcane harvest alone.

Figure 7 displays the dynamic treatment effects for relative ethanol consumption, emissions, and employment using event study plots. It is possible to observe an initial positive effect on relative ethanol consumption that dissipates over time, as well as an initial negative effect on emissions that also fades over time. This pattern confirms that the reduction in emissions resulting from the substitution of gasoline outweighs the increase in emissions associated with the adoption of the *flex* model. In the case of employment, the effect grows over time, which may indicate the presence of a spillover or multiplier effect along the supply chain.

Similar to Figure 7, Figure 8 displays the dynamic treatment effects on employment by sector: rural, industrial, and services. Figure 8a shows that the effect on rural employment increases over time. This result may be explained by the growing demand for corn in areas that previously did not produce it. In the case of industrial employment, the effect is positive in the initial years but fades over time, a pattern also observed in the service sector.

5 Discussion

Since the 1970s, with the launch of the Pro Álcool program, ethanol has served as an alternative to fossil fuels in Brazilian transportation. However, relying primarily on sugarcane, a geographically concentrated crop that poses challenges in terms of storage and transportation, ethanol's competitiveness has historically been limited to specific regions of the country, particularly the states in the Center-South.

In this context, the expansion of corn production and productivity in Brazil, combined with infrastructure bottlenecks that hinder its export, has supported the use of corn as an alternative feedstock for ethanol production. This shift has taken place both in existing sugarcane-based ethanol plants adapted to process corn (*flex* model) and in new facilities designed to produce ethanol exclusively from corn (*full* model).

This study aimed to assess the energy, environmental, and socioeconomic impacts of adopting *flex* and full corn ethanol production technologies in Brazil, using the doubly robust difference-in-differences methodology. The main findings indicate that the *full* model led to an increase in relative ethanol consumption and job creation in the municipalities where it was adopted, while the *flex* model contributed to a reduction in CO_2 emissions and also stimulated employment.

These results highlight the potential of corn ethanol technologies to reshape the energy landscape in Brazilian regions previously less integrated into the biofuel production chain. By decentralizing ethanol supply and fostering regional development, the adoption of *flex* and *full* models represents not only a strategic response to the logistical and environmental limitations of sugarcane-based production but also a promising pathway to expand the economic, social, and environmental benefits of ethanol in the country.

A key limitation of this study is the lack of consideration for potential spillover effects across neighboring municipalities. By focusing solely on the direct impacts within municipalities that adopted the flex or full corn ethanol technologies, the analysis may overlook indirect effects that could influence surrounding areas. Future research could address this limitation by incorporating spatial econometric techniques or models that explicitly account for intermunicipal linkages and spillover effects.

References

Anderson, L. (2009). Ethanol fuel use in brazil: Air quality impacts. *Energy & Environmental Science*, 2:1015–1037.

ANP (2025). Agência nacional do petróleo, gás natural e biocombustíveis (anp), sistema de preços da ANP. Acesso em: 18 jul. 2025.

Bothast, R. and Schlicher, M. (2005). Biotechnological processes for conversion of corn into ethanol. appl microbiol biotechnol. *Applied microbiology and biotechnology*, 67:19–25.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Cavalcanti, M., Szklo, A., and Machado, G. (2012). Do ethanol prices in Brazil follow Brent price and international gasoline price parity? *Renewable Energy*, 43(C):423–433.

Conab (2023a). Cana-de-açúcar - indústria. https://www.conab.gov.br/info-agro/safras/serie-historica-das-safras/itemlist/category/893-cana-de-acucar-industria.

Conab (2023b). Milho. https://www.conab.gov.br/info-agro/safras/serie-historica-das-safras/itemlist/category/910-Milho.

de Andrade Junior, M., Valin, H., Soterroni, A., Ramos, F., and Halog, A. (2019). Exploring future scenarios of ethanol demand in brazil and their land-use implications. *Energy Policy*, 134:1–12.

De Oliveira, F. C. and Coelho, S. T. (2017). History, evolution, and environmental impact of biodiesel in brazil: A review. *Renewable and Sustainable Energy Reviews*, 75(C):168–179.

Eckert, C., Frigo, E., Albrecht, L., Albrecht, A., Christ, D., Santos, W., Berkembrock, E., and Egewarth, V. (2018). Maize ethanol production in brazil: Characteristics and perspectives. *Renewable and Sustainable Energy Reviews*, 82:3907–3912.

El Montasser, G., Gupta, R., Martins, A. L., and Wanke, P. (2015). Are there multiple bubbles in the ethanol–gasoline price ratio of Brazil? *Renewable and Sustainable Energy Reviews*, 52(C):19–23.

Freitas, L. and Kaneko, S. (2011a). Ethanol demand in brazil: Regional approach. *Energy Policy*, 39(5):2289–2298.

Freitas, L. d. and Kaneko, S. (2011b). Ethanol demand under the flex-fuel technology regime in brazil. *Energy Economics*, 33(6):1146–1154.

Goldemberg, J., Coelho, S. T., and Guardabassi, P. (2008). The sustainability of ethanol production from sugarcane. *Energy Policy*, 36(6):2086–2097.

Kristoufek, L., Janda, K., and Zilberman, D. (2015). Co-movements of Ethanol Related Prices: Evidence from Brazil and the USA. CAMA Working Papers 2015-11, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.

Laurini, M. P. (2017). The spatio-temporal dynamics of ethanol/gasoline price ratio in brazil. *Renewable and Sustainable Energy Reviews*, 70:1–12.

Moreira, M., Seabra, J., Lynd, L., Arantes, S., Cunha, M., and Guilhoto, J. (2020). Socio-environmental and land-use impacts of double-cropped maize ethanol in brazil. *Nature Sustainability*, 3:1–8.

Neves, M. F. O. (2021). *Etanol de milho (livro eletrônico): cenário atual e perspectivas para a cadeia no Brasil*. UNEM.

Orellano, V., Souza, A., and Azevedo, P. (2013). Elasticidade-preço da demanda por etanol no brasil: Como renda e preços relativos explicam diferenças entre estados. *Revista de Economia e Sociologia Rural*, 51:699–718.

Pacini, H. and Silveira, S. (2011a). Consumer choice between ethanol and gasoline: Lessons from brazil and sweden. *Energy Policy*, 39(11):6936–6942. Asian Energy Security.

Pacini, H. and Silveira, S. (2011b). Consumer choice between ethanol and gasoline: Lessons from Brazil and Sweden. *Energy Policy*, 39(11):6936–6942.

Ritchie, H., Roser, M., and Rosado, P. (2022). Energy. *Our World in Data*. https://ourworldindata.org/energy.

Roth, J., C., S. P. H., Bilisnki, A., and Poe, J. (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244.

Sant'Anna, P. H. and Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of econometrics*, 219(1):101–122.

Silva, A. L. and Castañeda-Ayarza, J. A. (2021). Macro-environment analysis of the corn ethanol fuel development in brazil. *Renewable and Sustainable Energy Reviews*, 135.

Silva-Junior, C., Moreira Pessôa, A. C., Carvalho, N., dos Reis, J., Anderson, L., and Aragão, L. (2021). The brazilian amazon deforestation rate in 2020 is the greatest of the decade. *Nature Ecology & Evolution*, 5:144–145.

Unicadata (2023). Consumo. https://unicadata.com.br/listagem.php?idMn=11.

Unicadata (2024). Produção. https://unicadata.com.br/listagem.php?idMn=4.

Walter, A., Galdos, M. V., Scarpare, F. V., Leal, M. R. L. V., Seabra, J. E. A., Cunha, M. P. d., Picoli, M. C. A., and de Oliveira, C. O. F. (2014). Brazilian sugarcane ethanol: developments so far and challenges for the future. *Wiley Interdisciplinary Reviews: Energy and Environment*, 3(1):70–92.

Wilkinson, J. and Herrera, S. (2010). Biofuels in brazil: debates and impacts. *The Journal of Peasant Studies*, 37(4):749–768.

Appendix

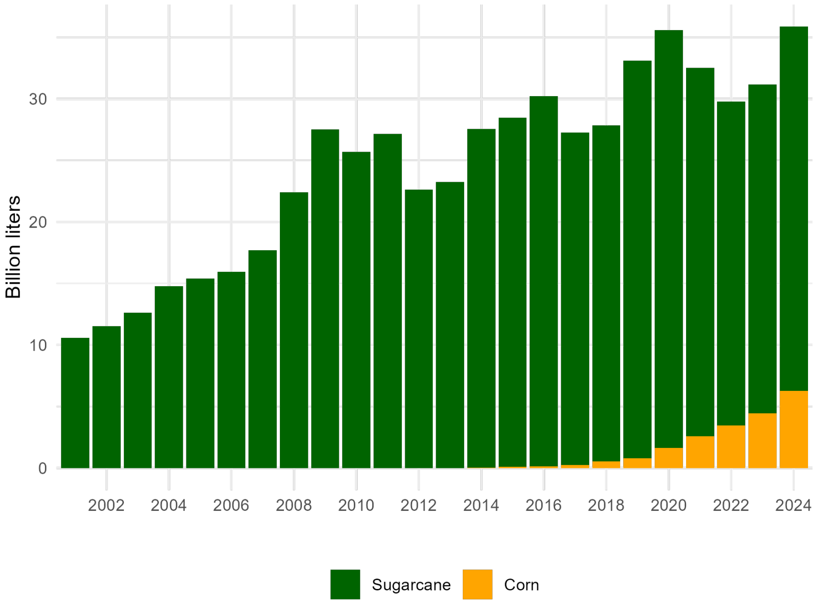


Figure 1: Ethanol production in Brazil

Data from Unicadata. Notes: Ethanol production, measured in billion liters, represents the sum of anhydrous and hydrous ethanol produced annually in Brazil.

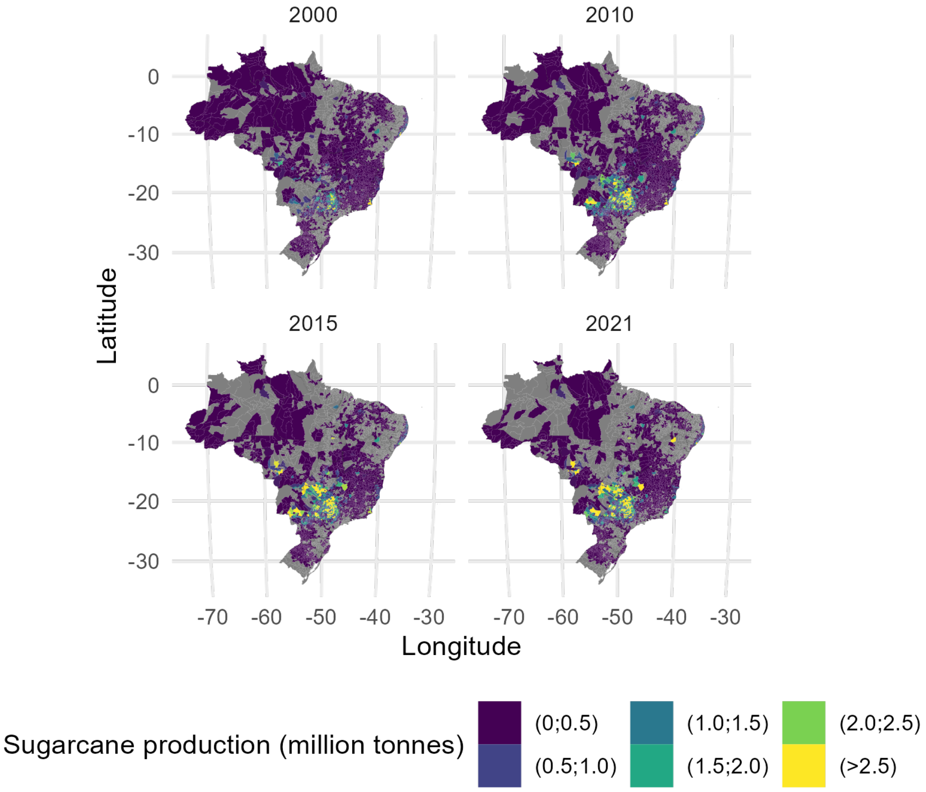


Figure 2: Sugarcane production by city

Data from Sidra-IBGE. Sugarcane production, measured in million tonnes, by city in Brazil.

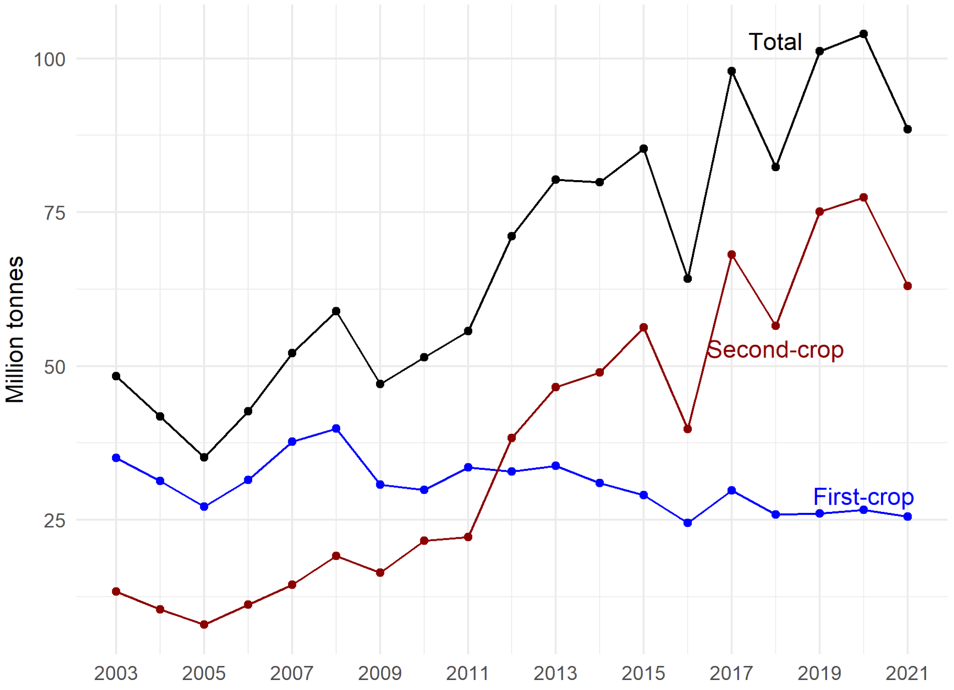


Figure 3: Corn production in Brazil.

Data from IBGE-Sidra. Corn production is measured in million tonnes. *First-crop* and *second-crop* denote distinct planting and harvesting cycles of corn in regions with multiple growing seasons per year.

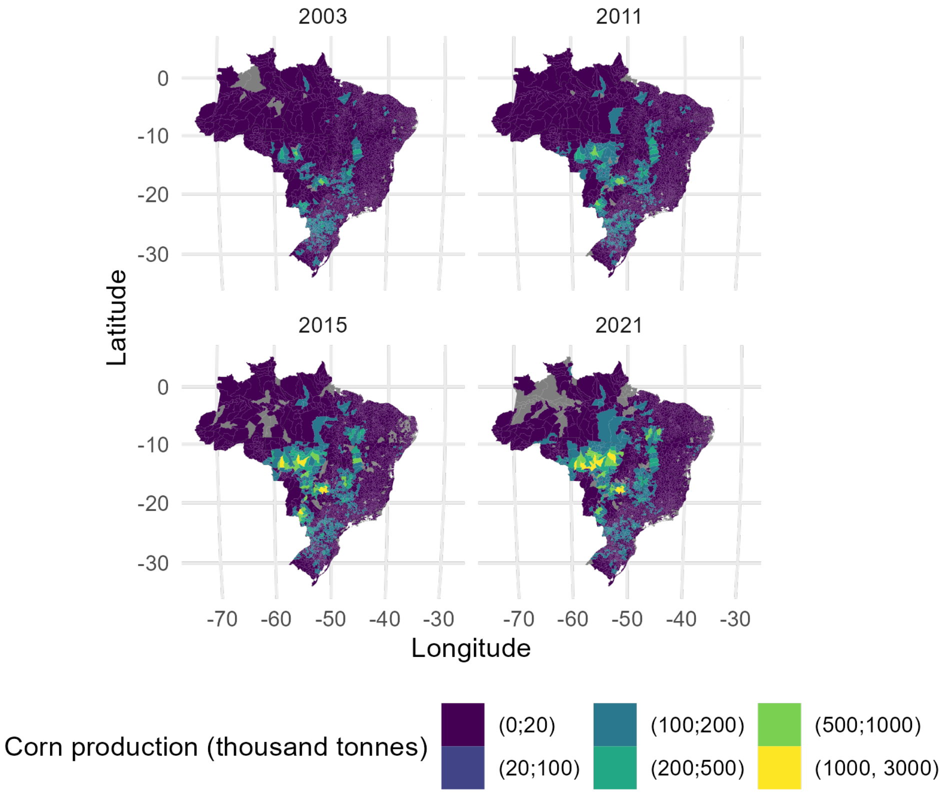
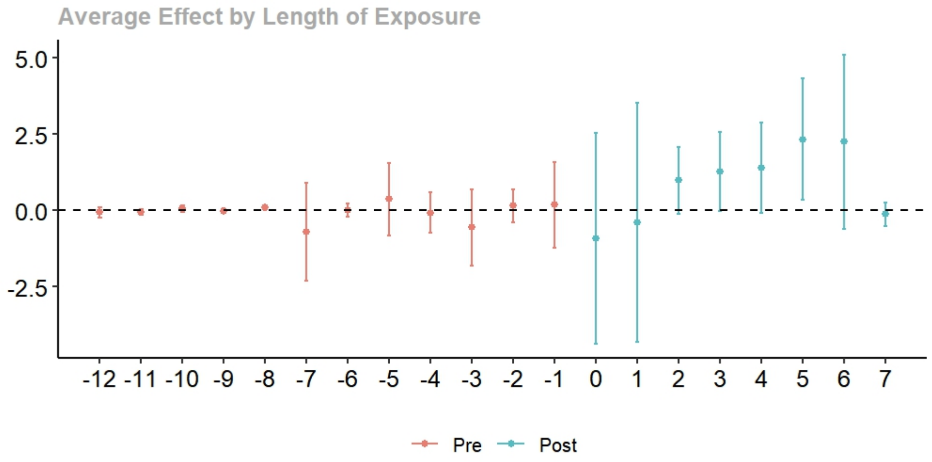
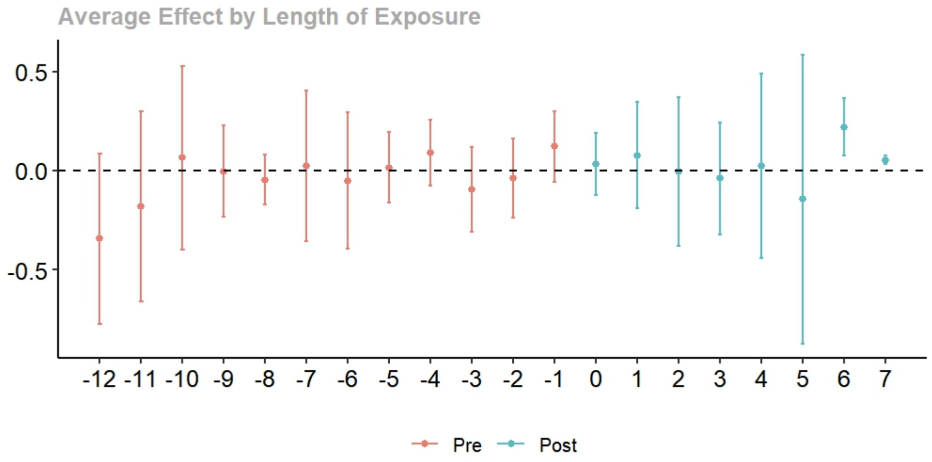


Figure 4: Corn production by city

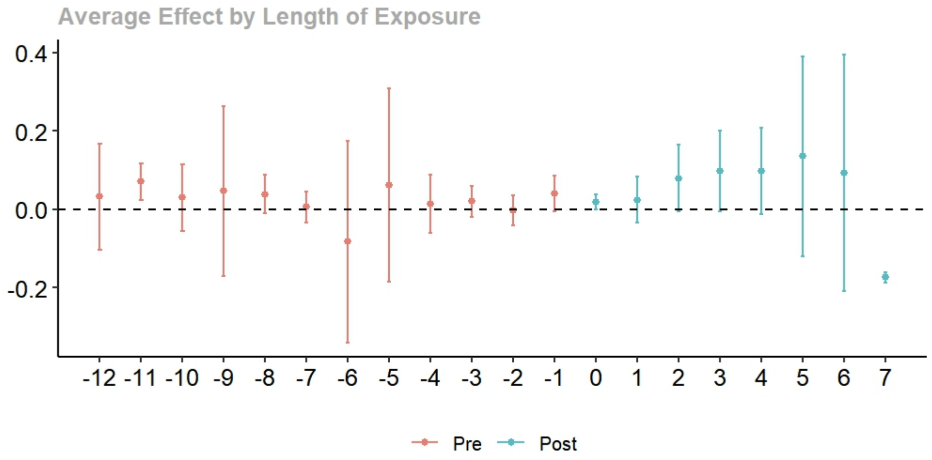
Data from Sidra-IBGE. Million production, measured in thousand tonnes, by city in Brazil.



(a) Relative Ethanol Consumption.

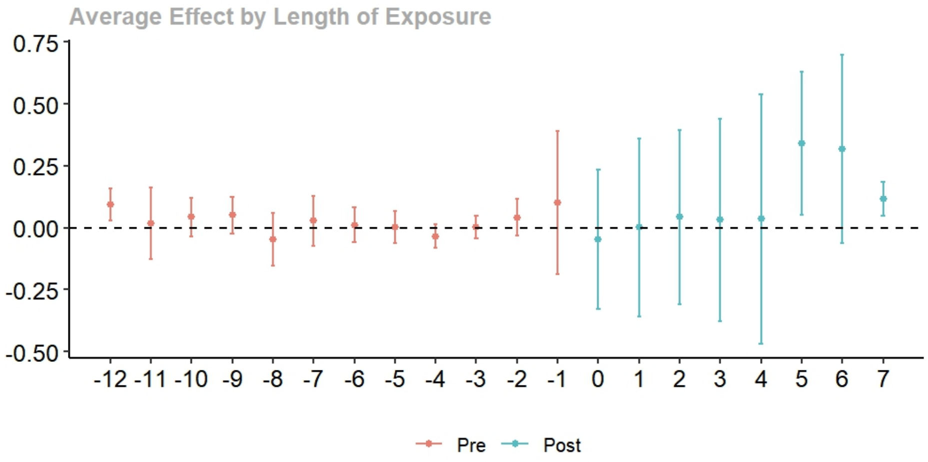


(b) CO_2 Emissions.

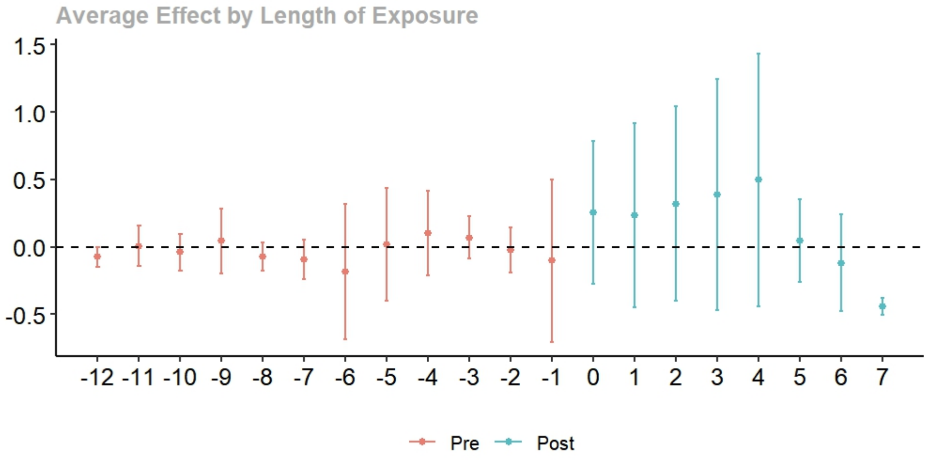


(c) Employment.

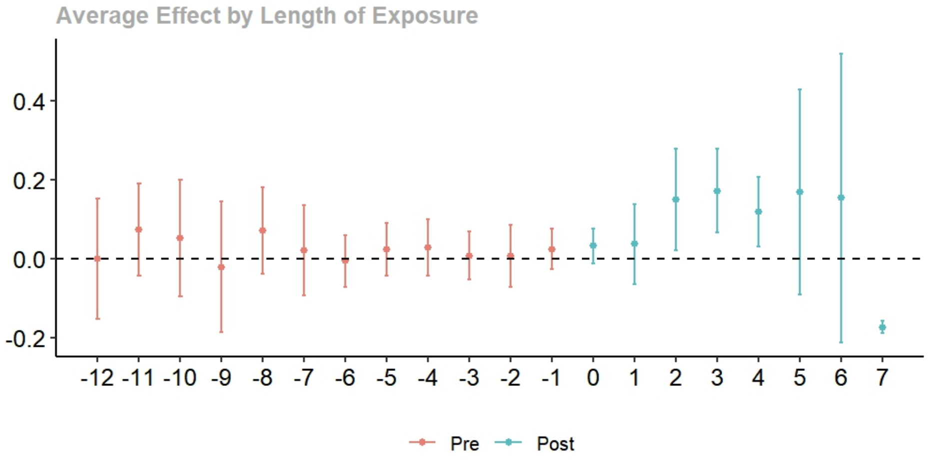
Figure 5: Event Study - Treatment: Adoption of the *full* model



(a) Rural Employment.

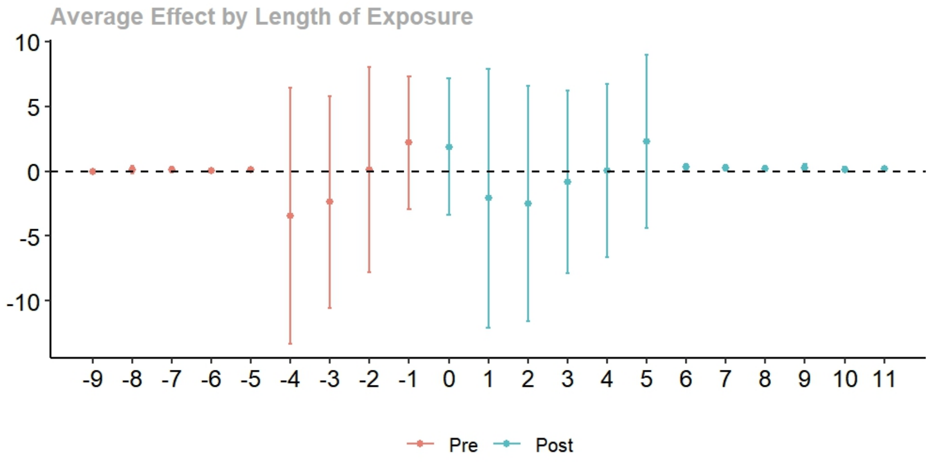


(b) Industrial Employment.

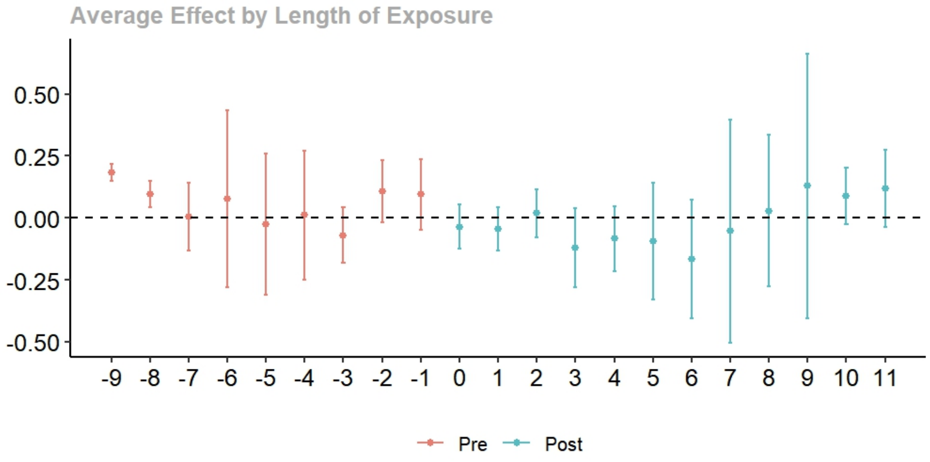


(c) Services Employment.

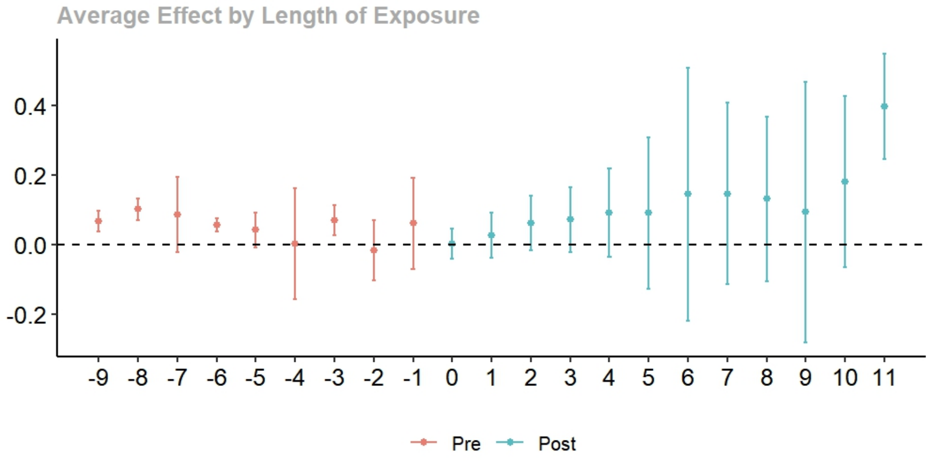
Figure 6: Event Study - Treatment: Adoption of the *full* model



(a) Relative Ethanol Consumption.

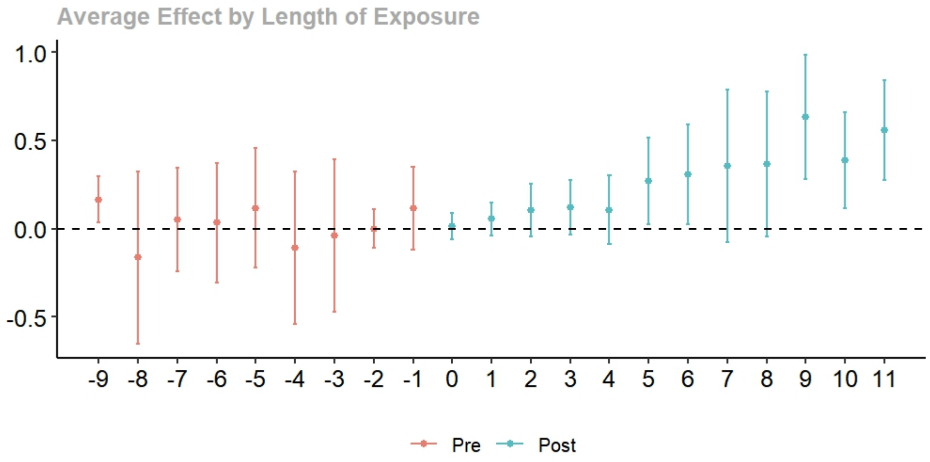


(b) CO_2 Emissions.

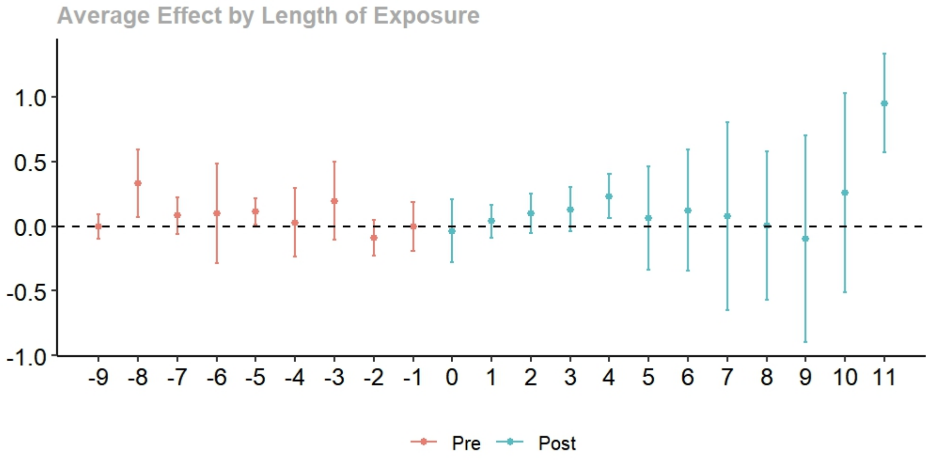


(c) Employment.

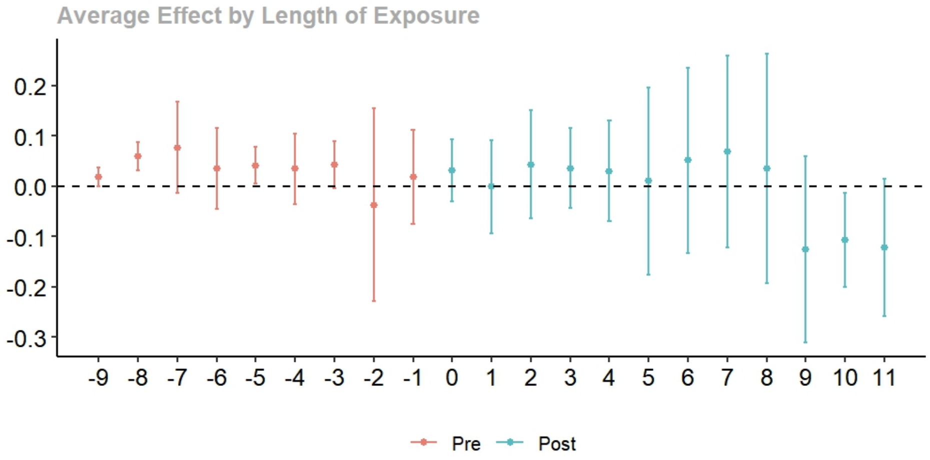
Figure 7: Event Study – Treatment: Adoption of the *flex* model



(a) Rural Employment.



(b) Industrial Employment.



(c) Services Employment.

Figure 8: Event Study - Treatment: Adoption of the *flex* model