Do Free Public Transport Impact Economic and Environmental Outcomes? Evidence from Brazil *

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Preliminary version—Latest version available here.

Abstract

Climate change poses significant challenges, with implications extending beyond environmental concerns to various economic variables. In this context, national and supranational institutions emphasize the need to reduce greenhouse gas emissions, prompting the development of climate mitigation policies. This study analyzes the environmental and economic impacts of a policy implemented by several Brazilian municipalities: the implementation of fare-free public transportation. Using a difference-in-differences approach with staggered treatment adoption, we find that fare-free transit reduces greenhouse gas emissions while boosting local employment levels. These findings suggest that transportation policies can generate absolute decoupling—a scenario where economic activity grows while greenhouse gas emissions decrease or remain stable. Further examination of the mechanisms behind these results indicates that individuals are not abandoning car usage due to these policies, but rather, there is a shift in the composition of employment within local economies.

JEL Classification: Q54, R11, J82.

Keywords: Transportation policy, Greenhouse gases emissions, Employment, Decoupling, Commuting costs, Structural transformation

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1 Introduction

Climate change stands as one of the most pressing issues of our time. The Sixth Assessment Report released by the Intergovernmental Panel on Climate Change (IPCC) (Shukla et al., 2022) underscores the urgency, revealing that anthropogenic greenhouse gas (GHG) emissions reached unprecedented levels over the past decade. This alarming trend not only threatens to elevate global temperatures but also portends significant economic repercussions, including income losses (Burke et al., 2015; Kahn et al., 2021), exacerbated spatial inequality (Cruz and Rossi-Hansberg, 2024), and shifts in economic activity (Desmet and Rossi-Hansberg, 2015; Conte et al., 2021).

To address this challenge, nations worldwide have rallied behind the Paris Agreement, a landmark accord forged during the 2015 United Nations Climate Change Conference (COP 21). In 2016, Brazil ratified its commitment to the Paris Agreement and in its official Intended Nationally Determined Contributions (iNDC), outlined its strategy, emphasizing emission reduction amidst continued population and GDP growth, alongside rising per capita income (Brazil, 2015). Following Jaramillo et al. (2022), which recognizes the implementation of free transport passes for the population as a possible mitigation policy, and motivated by Brazil's ambitious decoupling[1] objectives, our study seeks to investigate the efficacy of free public transport policies in affecting emissions and employment levels.

Theoretical ambiguity clouds the anticipated impact of such policies. While free public transport could potentially encourage commuters to switch from cars to buses (Dunkerley et al., 2018), which decreases GHG emissions, variations in public fares might also spur broader economic changes by reducing commuting costs, integrating informal workers into the labor market (Zárate, 2022) and increasing economic activity and emissions. Therefore, both the magnitude and the direction of the net effects are conceptually ambivalent.

We focus on municipalities that have universally adopted free public transport in Brazil. Leveraging the staggered adoption of this policy across multiple time periods, we employ a difference-in-differences approach to identify its effects on the outcomes of interest. Our findings suggest that free public transport policies can indeed foster decoupling in local economies. Our baseline estimates indicate a 3.8% increase in employment levels and a 4.3% reduction in greenhouse gas emissions, indicative of absolute decoupling. However, our analysis of potential mechanisms reveals that the results are not driven by a shift from cars to buses but rather by changes in job com-

[1] Hubacek et al. (2021) defines decoupling based on the relative speed of GDP growth with respect to greenhouse gases emissions. An absolute decoupling occurs when the emissions decline in absolute terms or are stable, while the economic activity grows. An relative decoupling occurs when the emissions grow in a lower rate than the economic activity.

position, with individuals transitioning from sectors associated with higher emissions to those with lower emissions.

We also conduct a cost-benefit analysis, evaluating both the costs associated with the policy implementation and its outcomes in relation to fiscal externalities and monetary effects stemming from reduced carbon emissions. Our benefit estimates are a lower bound for the true benefits and demonstrate that they significantly outweigh the costs across the majority of years.

Our study contributes to two strands of literature. Firstly, it contributes by analyzing transportation policies' impacts on greenhouse gas emissions, a vital component of mitigation strategies. While existing research has explored the effects of various policies on emissions, including subsidies (Qin and Zhang, 2015), congestion (Bharadwaj et al., 2017), vehicle types (Wang et al., 2018; Lin and Wu, 2021), and mode choices (Lin et al., 2021; Donna, 2021; Gillingham and Munk-Nielsen, 2019), our focus on free public transport policies offers a different perspective, given their distinct nature as a zero-price mode of transportation. Besides, this study is unique in studying whether free transportation policies can decouple economic activity from GHG emissions.

Secondly, we contribute to the literature exploring the relationship between commuting costs and employment dynamics. Recent studies in this field have investigated the impacts of commuting costs on job and sector decentralization (Baum-Snow, 2020; Tyndall, 2021; Gonzalez-Navarro and Turner, 2018). Our contribution lies in observing not only the impact on the general employment level[2], but also in highlighting a shift in the sector composition of cities as a whole, rather than solely the location of firms within specific sectors. This shift in sector composition aligns with the broader literature on structural transformation, particularly regarding the mechanism of transitioning from agriculture to urban jobs evident in our baseline results. Noteworthy works in this branch include those by Adamopoulos et al. (2022) and Lebrand (2022).

The subsequent sections of this work are organized as follows. Section 2 provides a concise institutional background on Brazil's public transport system, examining the subsidies and free public transport policies implemented at the local level. Section 3 outlines our data sources and sample selection procedure, while Section 5 presents the empirical strategy for identifying and estimating treatment effects. Section 6 presents our baseline findings, heterogeneous treatment effects, potential mechanisms, and robustness checks. Finally, Section 9 offers concluding remarks.

[2] Baum-Snow (2020) also identifies significant employment impacts, whereas the other studies primarily focus on evidence of spatial job redistribution.

2 Institutional Background

Urban public transportation system in Brazil is governed by the National Policy of Urban Mobility, which delineates the responsibilities of the federal, state, and municipal governments regarding the provision of public transportation.

The federal government oversees interstate urban transport, while the state government handles intercity urban transport. Municipalities are tasked with providing public transport within their jurisdiction. Public transportation at these three levels can be directly operated by the government or through concession mechanisms via bidding, which is the prevailing practice in Brazil.[3]

In terms of transportation modes, Brazil's public transport primarily comprises buses and rail services, with buses being the more prevalent mode – 85.3% of public transport journeys are made by bus. Consequently, this study will focus on municipal bus systems.

Free public transport has emerged as an increasingly prevalent policy in Brazil, with many municipalities adopting it, spurred by the COVID-19 pandemic. Furthermore, with its inclusion in the Workers Party's official agenda, it has become a priority policy for the incumbent federal government. The National Association of Public Transport Companies (*Associação Nacional das Empresas de Transportes Urbanos*, or NTU) identifies five main public transport fare policies implemented in Brazilian municipalities:

1. **Universal free public transport:** All users have unrestricted access to all bus routes every day without charge.

2. **Partial free public transport for specific users:** Certain user categories are exempt from bus fares.[4]

3. **Partial free public transport on specific days:** Users incur no charges on certain days of the week.[5]

4. **Partial free public transport in specific regions:** Bus routes serving specific areas within municipalities are fare-free.[6]

5. **Subsidies:** This category encompasses various policies. Local governments may

[3]Direct provision is limited to a few public entities operating in small cities where user numbers are insufficient to attract private firms, or to certain rail lines, such as the *Companhia do Metropolitano de São Paulo*, a mixed economy company responsible for managing the São Paulo Metropolitan Area subway system.

[4]For example, workers in shopping malls in São Luís, Maranhão, after 10 pm.

[5]For instance, São Paulo implemented free transport on Sundays and specific holidays.

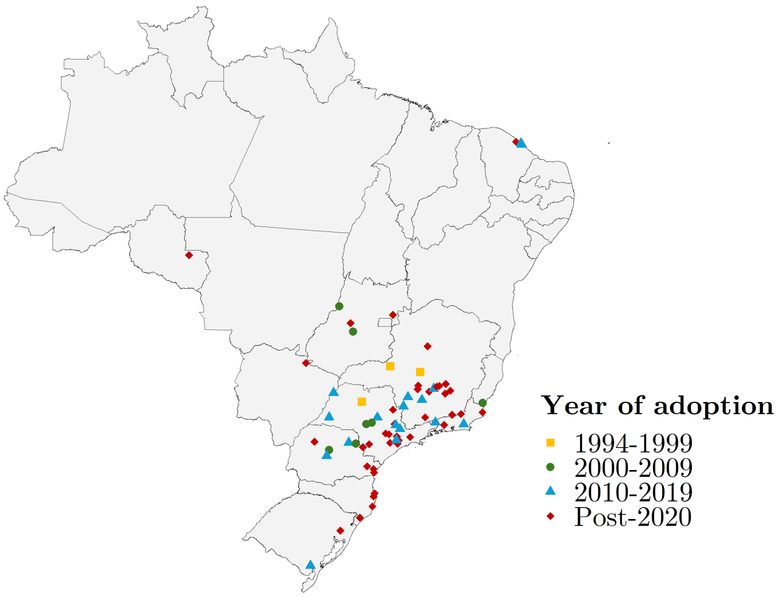
[6]Such as buses serving slums and villages in Belo Horizonte, Minas Gerais.

subsidize specific user groups[7], implement variable subsidies to reduce user fares, or provide lump-sum subsidies based on total system costs.

In regard to the financing of the policy, NTU highlights that the bulk of the funding is sourced from municipal budgets.

Figure 1 illustrates the geographical distribution of municipalities implementing the first type of policy mentioned above. As depicted, these cities are concentrated in the South and Southeast regions, with fewer instances in the North, Northeast, and Midwest regions.

Figure 1: Spatial distribution of municipalities adopting universal free public transport

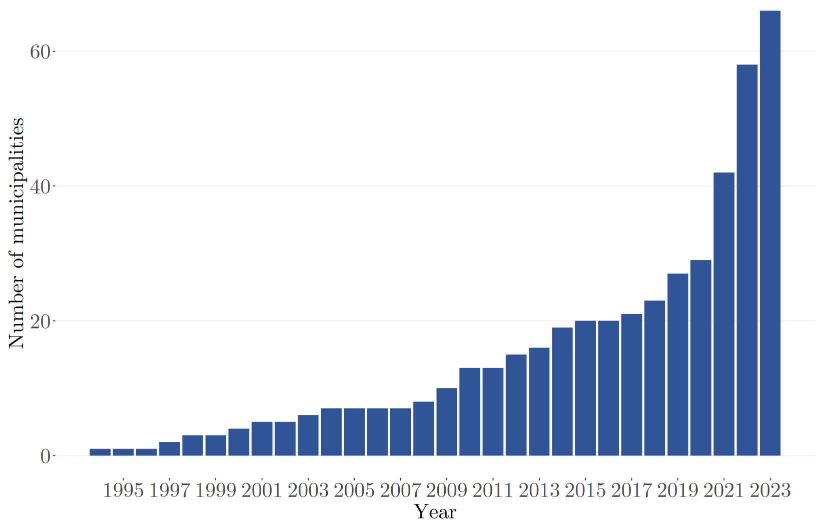


Notes: This figure displays the spatial distribution of all of the municipalities that adopt the universal free public transport policy, by year of adoption. Yellow dots represent units that were first treated between 1994 and 1999, green dots represents units that were treated between 2000 and 2009, blue dots represent units that were first treated between 2010 and 2019 and red dots represent the units that were treated after 2020. The internal boundaries of are the states of Brazil.

Figure 2 depicts the adoption trend of the universal free public transport policy over time. The first instance occurred in 1994 in Monte Carmelo, Minas Gerais, with subsequent adoptions up to 2023. This graph underscores the staggered adoption pattern and indicates a surge in policy adoption following the onset of the COVID-19 pandemic.

[7] For example, students in São Paulo pay half the standard fare.

Figure 2: Number of municipalities adopting a universal free public transport policy, by year



Notes: This figure displays the cumulative number of municipalities adopting the universal free public transport in Brazil. The first treated unit adopted the policy in 1994 and the last one does it in 2023.

3 Data

The primary data on emissions is sourced from the System of Estimates on Emissions and Removals of Greenhouse Gases (SEEG). [8] SEEG provides sector-specific emission calculations by municipality in Brazil, following guidelines from IPCC and the Brazilian National Inventory of Anthropogenic Emissions and Removals of Greenhouse Gases, as elaborated by the Ministry of Science and Technology. The data from 1990 to 2022. [9]

SEEG's methodology involves the combination of economic activity variables and emission factors for the construction of emissions. Allocation at the subnational level is based on local emission-generating activities. For more detailed information on SEEG's methodology, refer to De Azevedo et al. (2018).

Our emissions outcomes are expressed as net CO_2-equivalent in terms of Global Warming Potential over 100 years, following the Fifth Assessment Report from IPCC (GWP100-AR5). CO_2-equivalent is a summation of the emissions of different greenhouse gases, weighted by their global warming potential. The three main greenhouse gases, CO_2, CH_4, and N_2O, receive weights of 1 (by construction), 28, and 256, respectively. Data from EDGAR needed to be aggregated to the municipalities in Brazil.

[8] The version utilized for this research is 11.1

[9] Although the raw data contains records dating back to 1970, there is a structural break in the series. SEEG began reporting data on land use change only from 1990 onwards. Therefore, we have chosen to restrict the sample to the period with a standardized methodology.

However, due to changes in Brazil's internal boundaries resulting in the creation of new municipalities, we opted to aggregate the data at the Minimum Comparable Area (*Área Mínima Comparável*, or AMC) level. An AMC consists of a set of municipalities whose borders were constant over the study period. The emissions of an AMC are calculated by summing the emissions from the municipalities that compose it.

Employment data was obtained from administrative data provided by the Ministry of Labor in Brazil in the *Relação Anual de Informações Sociais* (RAIS) dataset. RAIS encompasses all formal sector employment relationships in Brazil.[10] Publicly available data includes firm-level or employment relationship-level details, enabling identification of the municipality where the firm is situated. Given the yearly time dimension of our panel, the employment outcome chosen is the stock of employees in a given AMC at year-end. RAIS also facilitates identification of the firm's sector, which we utilize to comprehend the mechanisms underlying the results. The primary reference for sectors is the National Classification of Economic Activities (*Classificação Nacional de Atividades Econômicas*, or CNAE) from the *Instituto Brasileiro de Geografia e Estatística* (IBGE), version 1.0 from 1994 onwards.[11] Sector aggregation follows the scheme outlined in Table 1.

[10] All firms registered in the National Registry of Firms (*Cadastro Nacional de Pessoas Jurídicas*, or CNPJ) in Brazil are required to report their employee count for each year, even if it's zero. The only exceptions are individual entrepreneurs without any employees.

[11] Although the latest CNAE version is 2.0, released in 2006, we restricted the sample to 1994 onwards in sectoral analyses as CNAE 1.0 first appears in RAIS in 1994.

Table 1: Sector aggregation

Aggregate sector	CNAE 1.0 section
Industry	C and D
Construction	F
Trade	G
Services	H, J, K, L, M, N, O and P
Agriculture	A
Transportation	I

Notes: This figure illustrates sector aggregation based on CNAE 1.0 sections. The sections are arranged sequentially: Section A includes agriculture, livestock, forestry, and forest exploitation, as well as transportation, storage, and communications. Following A, Section C denotes extractive industries, while Section D represents manufacturing industries. Continuing, Section F pertains to construction, and Section G encompasses trade and repair of motor vehicles, personal, and household items. Section H focuses on lodging and food, and Section J relates to financial intermediation. Further, Section K involves real estate activities, rentals, and services provided to companies, whereas Section L covers public administration, defense, and social security. Subsequently, Section M deals with education, followed by Section N, which encompasses health and social services. Section O comprises other collective, social, and personal services, and Section P denotes domestic services.

In Section 2, we detailed the types of urban transportation policies implemented by municipalities. All policies except universal free public transport imply a highly heterogeneous treatment allocation definition because within the same category, municipalities may implement the policy on different days, for different users, or using different types of subsidy. To standardize the treatment allocation definition, we consider an AMC treated if any of its municipalities adopt universal free public transport.

We also utilize two auxiliary datasets to comprehend the mechanisms driving the results. The first contains sales data, in liters, of ethanol and gasoline in each municipality, provided by the National Agency of Petroleum, Natural Gas, and Biofuels (*Agência Nacional do Petróleo, Gás Natural e Biocombustíveis do Brasil*, or ANP). This data spans from 1990 to 2022, requiring standardization of municipality names across years before aggregation at the AMC level. The second dataset comprises the stock of automobiles in each municipality, provided by the Transport Ministry under the National Secretary of Transit (*Secretaria Nacional de Trânsito*, or Senatran).

To perform the cost-benefit analysis, we utilize microdata from the Brazilian Household Budgetary Survey (*Pesquisa de Orçamentos Familiares*, or POF) 2017-2018. The POF 2017-2018 microdata is a survey conducted by IBGE and comprises a detailed description of individual expenses and income. Additionally, other macroeconomic data, such as the inflation index IPCA (*Índice de Preços ao Consumidor Amplo*) provided by IBGE and the nominal exchange rate provided by the Brazilian Central Bank, are also utilized in our calculations.

4 Sample Selection

Initially, we exclude municipalities from the control group that implement any form of partial free public transport and subsidy. To construct a control group more analogous to the treated units, we further limit it to the sample of AMCs with a population no greater than the largest treated AMC in the 1991 Brazilian Census, computed before the first unit becomes treated. Moreover, we retain only AMCs situated in states with at least one treated unit.

Our outcomes are presented as natural logarithms. This allows for interpretation of results as percentage variations relative to the scenario without treatment. Consequently, depending on the outcome, it was necessary to exclude some units with a value lower or equal than zero for a specific outcome.[12]

Table 2 illustrates the procedures described above. After filtering the control group, we obtain 3,733 AMCs. With the population filter, this number reduces to 3,730. Subsequently, by retaining only AMCs from states with at least one treated unit, we arrive at 2,731 AMCs. Finally, upon dropping AMCs with an outcome value of zero, the number of units in the final column is reached.

[12] Given the fact that SEEG considers net emissions, some AMC may present negative values for emissions in a given period.

Table 2: Number of observations in each step of the sample selection, by outcome

		Type of selection			
	Original	Control	Population	States	> 0
Emissions	3,800	3,733	3,730	2,371	2,308
Total employment	3,800	3,733	3,730	2,371	2,361
Stock of cars	3,800	3,733	3,730	2,371	2,369
Sectoral employment					
Industry	3,800	3,733	3,730	2,371	1,982
Construction	3,800	3,733	3,730	2,371	977
Trade	3,800	3,733	3,730	2,371	2,203
Services	3,800	3,733	3,730	2,371	2325
Agriculture	3,800	3,733	3,730	2,371	2162
Transportation	3,800	3,733	3,730	2,371	2,213
Sales by type of fuel					
Gasoline	3,800	3,733	3,730	2,371	2,162
Ethanol	3,800	3,733	3,730	2,371	1,860

Notes: This table illustrates the sample selection procedure in terms of number of observations. All datasets begin with a number of 3,800 AMC. The column "Control" shows the number of observations that left after removing from the control group all AMC that implement any type of free public transport or subsidy. The column "Population" denotes the number of observations left after removing all the AMC that have population higher than the largest treated AMC. The column "States" shows the number of observations left after removing the Brazilian states that do not have at least one treated unit. Finally, column "> 0" shows the final number of AMC in the sample used for the estimation of treatment effects, where we removed outcome-specific AMC that presented at least one observation equal to zero.

Table 3 presents descriptive statistics for baseline characteristics of the final sample used in estimating treatment effects for each outcome.

For emissions, total jobs, population, and fuel sales, data from the first available year (1990, 1985, 1991[13]) and 1990, respectively, are shown. Employment composition data is presented for 1994, the same year as the first treated unit, due to data restrictions. A similar constraint applies to stock of cars outcomes, with data displayed for

[13] Population data is available before 1991, but we reference the population from the latest available Census when the first unit was treated, which is the 1991 Brazilian Census.

2002.

On average, treated units exhibited higher emissions levels than control units and also demonstrated higher dispersion. Moreover, they had more jobs, cars, and consumed more gasoline and ethanol, yet the shares of each fuel type in total consumption were very similar. The two groups were comparable in their shares of industry, trade, agriculture, and other sector jobs, but diverged in terms of the proportion of construction, services, and transportation jobs. Lastly, treated units were notably more urban than control units.

Table 3: Descriptive statistics of the AMC baseline characteristics

	Treated		Control	
	Mean	Std. Deviation	Mean	Std. Deviation
Emissions	1,530.11	8,031.70	276.98	636.20
Total of jobs	3,652	4,878	2,778	9,124
Stock of cars	6,546	9,076	3,994	11,347
Fuel sales	8,640	20,587	4,415	11,741
Total population	58,194	140,602	28,435	68,434
Employment composition				
Industry	0.27	0.2	0.23	0.19
Construction	0.02	0.02	0.04	0.06
Trade	0.11	0.07	0.11	0.08
Services	0.38	0.17	0.45	0.23
Agriculture	0.13	0.12	0.18	0.17
Transportation	0.04	0.05	0.02	0.04
Other sectors	0.06	0.09	0.05	0.07
Fuel sales composition				
Gasoline sales	0.55	0.08	0.57	0.11
Ethanol sales	0.45	0.08	0.44	0.1
Population composition				
Urban population	0.75	0.18	0.54	0.22
Rural population	0.25	0.18	0.46	0.22

Notes: This table provides an overview of the baseline characteristics of the AMC by treatment group, with all statistics referencing the initial year available in the dataset. As a result, emissions data pertains to 1970, total job figures to 1985, car stock to 2002, fuel sales (including composition) to 1990 and employment composition shares for each sector reflect the scenario in 1994. The exception are population statistics. Despite the availability of older data, we opted to reference the most recent Brazilian Census preceding the treatment of the first unit for them. Emissions are expressed in 10^3 tons of CO_2-equivalent.

5 Empirical Strategy

Our setting involves a scenario where some treated units adopt universal free public transport in different years, indicating a staggered adoption scenario. Furthermore, there are no instances of municipalities ceasing treatment implementation after some years, which implies that treatment is irreversible. The parameters of interest for this study are Average Treatment Effects on the Treated (ATT).

However, treatment is not exogenous. For instance, mayors and local legislators may adopt universal free public transport for political reasons. Additionally, municipalities may adopt treatment based on some correlated non-observable factors.

Given these factors, we chose to employ the methodology proposed by Callaway and Sant'Anna (2021), as it identifies our main parameters of interest and estimates them without bias, under assumptions to be discussed below. Additionally, it enables heterogeneity exercises based on time elapsed since treatment, and across treatment cohorts and calendar years. Let G denote the group of a treated unit g (i.e., the time it was first treated), $\mathcal{G}$ denote the support of G excluding the maximum G, T denote the number of time periods, and $ATT(g,t)$ denote the ATT in t for units that were first treated in period g. Then, for each $g \in G$, define:

$$\theta_{at}(g) := \frac{1}{T-g+1} \cdot \sum_{t=g}^{T} ATT(g,t) \tag{1}$$

This represents the treatment effect for a specific treatment cohort. These parameters are useful for exploring whether heterogeneity exists between early and later treated units. Furthermore, our main parameter of interest can be summarized as an aggregation of the parameters from Equation (1), as per the recommendations from Callaway and Sant'Anna (2021):

$$\theta^{O} := \sum_{g \in \mathcal{G}} \theta_{at}(g) \cdot P(G=g|G<T) \tag{2}$$

Thus, θ^{O} represents the average effect of participating in the treatment experienced by all units that ever participated in the treatment.

To analyze whether treatment effects are influenced by local business cycles, we examine treatment effects by calendar year. Thus, for each $t \in \{1,\dots,T\}$, we are also interested in:

$$\theta_{ag}(t) := \sum_{g \in \mathcal{G}} \mathbf{1}\{t \geq g\} \cdot P(G=g|G \leq t) \cdot ATT(g,t) \tag{3}$$

Finally, we define event-study-like parameters, useful for inspecting the existence of parallel trends between treated and control units before treatment takes place. Let e denote the time elapsed since treatment adoption. Then, for each possible e, the aforementioned parameters can be described as follows:

$$\theta_{es}(e) := \sum_{g \in \mathcal{G}} \mathbf{1}\{g + e < T\} \cdot P(G = g | G + \epsilon < T) \cdot ATT(g, g + e) \tag{4}$$

6 Results

In the baseline results, we estimate the treatment effects of adopting universal free public transport on GHG emissions of the AMC and on employment. Given the large number of AMCs that adopt the policy during the COVID-19 pandemic, we utilize a sample that includes 2020, 2021, and 2022 for emissions and 2020 and 2021 for employment.

Table 4 presents the baseline results, where the treatment effects are estimates of the parameter defined in Equation (2). The treatment effects indicate that the policy had a negative and significant effect on emissions and a positive and significant effect on employment. Specifically, the universal free public transport reduced emissions by 4.3% and increased the stock of jobs by 3.8%, supporting the idea that it can generate an absolute decoupling in local economies. Compared to the literature, the magnitude of the estimated effect on emissions is substantial: Lin et al. (2021) estimate a reduction in greenhouse gases equivalent to 1.7% of China's transport sector emissions. Our estimate accounts for more than twice of their estimated effect and is defined in a broader scope, considering emissions from all sectors. Regarding employment, our estimated treatment effect represents approximately one quarter of the effect estimated by Hernandez-Cortes and Mathes (2023) for the impact of renewable energy projects on employment. In terms of the impact of transportation on local employment levels, our results suggest a positive impact of the policy. In contrast, Tyndall (2021) found a negative impact on aggregate metropolitan employment for another type of policy (light rail transit expansion).

Table 4: Treatment effects on emissions and employment

	GHG emissions	Employment
Treatment effect	-0.043^{*}	0.038^{***}
	(0.022)	(0.011)
Units	2308	2361
Treated units	56	41
Groups	20	19

Notes: This table presents the estimates of the overall treatment effects on emissions and employment, defined as in Equation (2). The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021). Standard errors, clustered at the unit level, are presented in parentheses. Additionally, the table displays the total number of units used in the estimation, along with the number of treated units and treated groups. Significance levels are denoted as follows: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

6.1 Heterogeneous Treatment Effects by Length of Exposure to the Treatment

As mentioned earlier, we are also interested in other causal parameters that can shed light on the behavior of the treated units. We begin by discussing dynamic treatment effects presented in Equation (4), which allows for the visual evaluation of pre-treatment trends and also presents whether the treatment effect is increasing, decreasing, or constant as the time since treatment adoption increases.

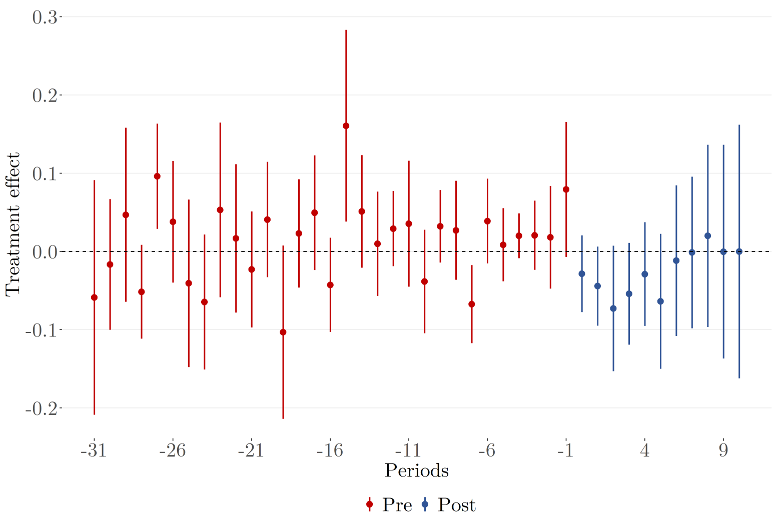
Figure 3a presents the estimates for those parameters. As we can see, for the vast majority of the pre-treatment periods, there is no difference between the emissions trends of the treated and control groups. Also, it suggests that the magnitude of the effect in absolute terms increases after the treatment adoption, but this result should be interpreted with caution due to compositional changes that influence the treatment effect.

Callaway and Sant'Anna (2021) provide a discussion about the compositional changes that might be associated with this type of heterogeneity. In our setting, the most prominent negative treatment effects are concentrated in cohorts that were treated near the end of our sample, as indicated in Figure 4a. This implies that the pattern displayed in Figure 3a can also be generated by the fact that we do not observe the effect on those units for so long.

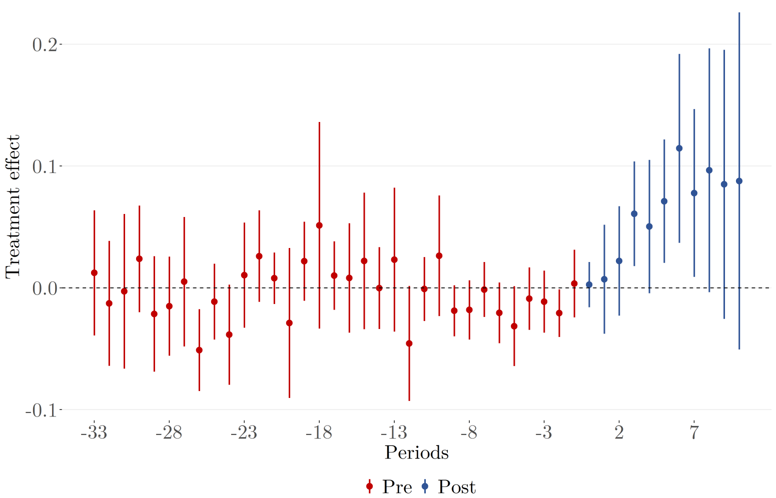
Figure 3b shows the estimates of the dynamic treatment effects on employment. We can see that there is no strong evidence of difference in pre-treatment trends between the treated and control groups. Also, it suggests that there might exist an increasing pattern in the treatment effect as time since treatment increases, with the possibility of reaching a plateau after some periods. However, again, we need to take into consideration the fact that this pattern might be generated by the same compositional changes mentioned above.

Figure 3: Heterogeneous treatment effects by length of exposure to the treatment

(a) Emissions



(b) Employment



Notes: This figure presents the estimates of the dynamic treatment effects from Equation (4), both pre and post treatment. Figure 3a presents the dynamic treatment effects on emissions, while Figure 3b presents the dynamic treatment effects on employment. The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021) using a varying base period. Vertical lines represent the 90% confidence intervals.

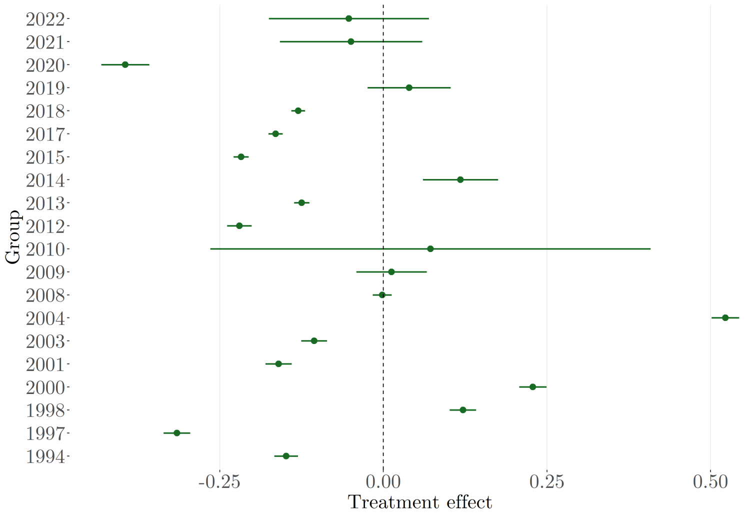
6.2 Heterogeneous Treatment Effects by Treatment Group

Figure 4a presents estimates for the parameters defined in Equation (1). For the majority of the treated cohorts, the policy had a negative effect on emissions, with only a few exceptions, such as the treated groups of 1998 and 2000. This indicates that the treatment effect is not strongly dependent on whether the cohort was early or later treated, however treated cohorts that were first treated in the pandemic seem to experience fewer benefits from the policy in terms of emissions.

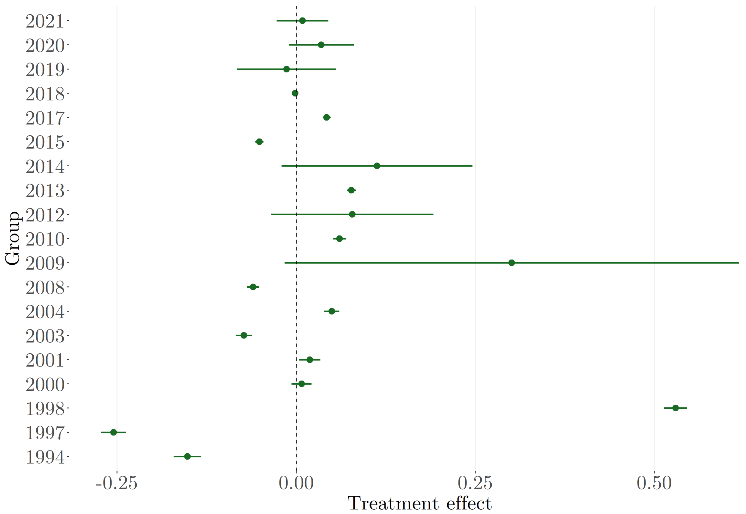
Figure 4b presents the estimates for the treatment effect on employment by treatment cohort. The vast majority of the treated cohorts face a treatment effect that is aligned with the overall treatment effect. However, especially for some early treated units, the estimated treatment effect is negative. Also, again we see that the units that were first treated during the pandemic are not positively affected in terms of employment by the policy.

Figure 4: Heterogeneous treatment effects by treatment group

(a) Emissions



(b) Employment



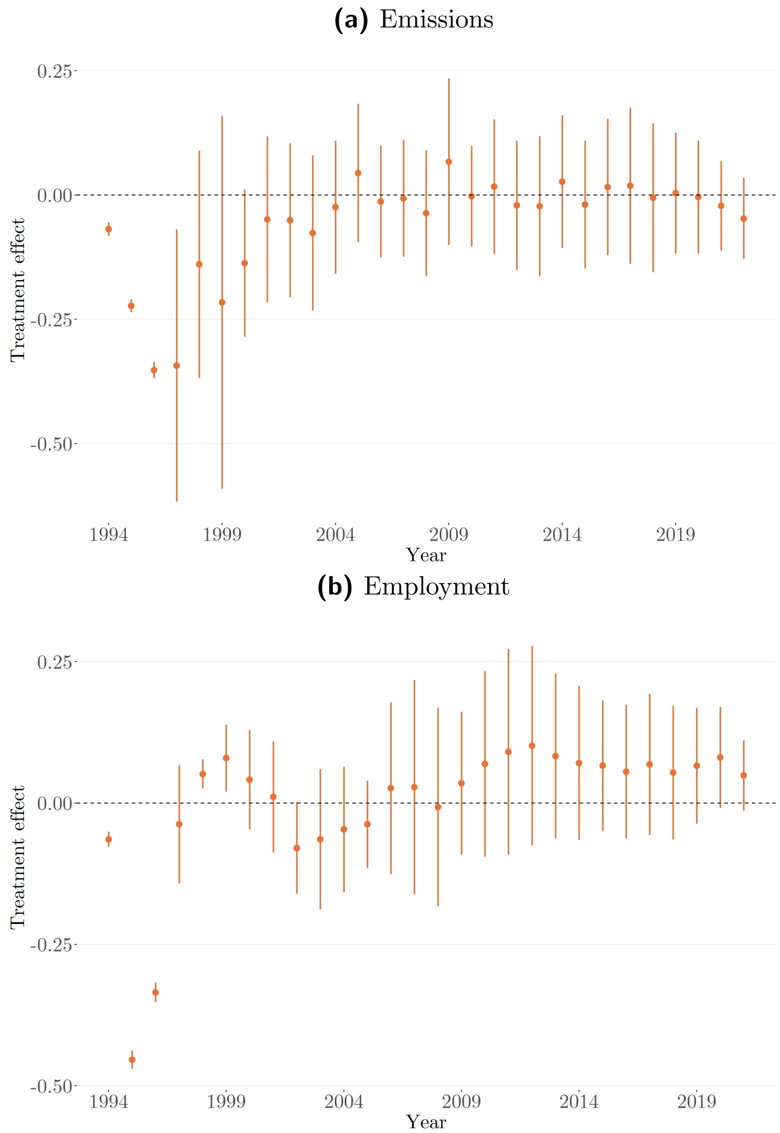
Notes: This figure presents the estimates of the group treatment effects from Equation (1). Figure 4a presents the group treatment effects on emissions, while Figure 4b presents the dynamic treatment effects on employment. The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021) using a varying base period. Horizontal lines represent the 90% confidence intervals.

6.3 Heterogeneous Treatment Effects by Year

Finally, Figure 5a presents the estimates for the parameter of Equation (5a). The pattern observed in the figure indicates that, although the context when the AMC was first treated seems to have a small impact on the treatment effect, the local economic cycle as a whole seems to be relevant. We observe an oscillation of the treatment effects, with negative effects during the 90's, an absolute reduction of the effects during the decade between 2000 and 2009, and a stability during the next decade.

Figure 5b displays the estimates for the same treatment effects on employment, which have a similar pattern to the estimates for emissions. One possible explanation of this pattern is the relation between emissions and economic growth, which is called "Environmental Okun's Law" by Cohen et al. (2017).

Figure 5: Heterogeneous treatment effects by year



Notes: This figure presents the estimates of the treatment effects by calendar year from Equation (3). Figure 5a presents the dynamic treatment effects on emissions, while Figure 5b presents the dynamic treatment effects on employment. The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021) using a varying base period. Vertical lines represent the 90% confidence intervals.

7 Potential Mechanisms

There is an *a priori* theoretical ambiguity in the direction of the causal effect of universal free public transport on emissions. This is due to the fact that it can affect both individual choices in terms of (i) commuting and (ii) the local economic activity.

On one hand, a reduction in the public fare can induce an increase in the demand for public transport system, as described by Dunkerley et al. (2018). If this increase is generated by individuals switching from cars to buses, we should expect a negative effect on emissions.

However, public fare variations can also change the local economic activity. Zárate (2022) points out that a reduction in commuting costs can allow the inclusion of individuals that were previously occupied in informal activities switch to the formal labor market, being employed in firms with higher productivity. Given the construction of the emissions data, this channel is expected to increase emissions at the local level.

The net effect of these two channels (commuting and local economic activity) is not clear. With this section, we aim to show that the first channel is not operating in this specific policy and the result is being driven by something closer to the second mechanism.

If individuals switch from private transportation to public transportation because of the policy, we expect that at least one of the two outcomes below:

1. **Stock of automobiles:** part of the automobile fleet would become less useful as individuals choose to use public transport. Depreciation and maintenance costs could lead them to sell these cars.

2. **Fuel sales:** one might argue that individuals could sell the car within the AMC, so that the stock of automobiles would not change. However, in equilibrium, we expect that the usage of cars would decrease, implying a reduction in the consumption of fuels.

Table 5 presents the estimates of the overall treatment effect from Equation (2) on the stock of automobiles, and gasoline and ethanol sales. For all three outcomes, the effect is not statistically significant.[14]. This suggests that the first channel is not operating in Brazil: individuals who used to use cars keep using them after the policy implementation.

[14] We do not use diesel as an additional outcome for two reasons. First, private cars in Brazil typically use either gasoline or ethanol (or both, in cars of type flex). According to the National Association of Producers of Vehicles (*Associação Nacional dos Fabricantes de Veículos Automotores*, or ANFAVEA), in 2022, 85.8% of the sales of automobiles in Brazil were either fueled by gasoline or of type flex. Also, diesel is also used for industry, implying that its series would be influenced not only by the switch from cars to buses but also by the economic activity.

The dynamic treatment effect estimates for the stock of automobiles, and gasoline and ethanol sales, are displayed in Figure A.3a in the Appendix. Overall, there appears to be no discernible difference in the pre-treatment trends between the treated and control groups.

Table 5: Treatment effects on stock of automobiles and fuel sales

	Stock of Automobiles	Gasoline sales	Ethanol sales
Treatment effect	0.014	0.121	−0.01
	(0.026)	(0.101)	(0.008)
Units	2,162	1,860	2,364
Treated units	55	52	52
Groups	20	19	15

Notes: This table presents the estimates of the overall treatment effects as defined in (2) on the stock of automobiles, gasoline sales and ethanol sales. The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021). Standard errors, clustered at the unit level, are presented in parentheses. Additionally, the table displays the total number of units used in the estimation, along with the number of treated units and treated groups. Significance levels are denoted as follows: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Then, we aim to find evidence that supports the second channel. In order to do so, we use sectoral employment data. The treatment effects of the policy are presented in Table 6. The results are not statistically significant for all but two of the sectors: construction and agriculture. We find that employment in construction is increasing, while the employment in agriculture is decreasing.

These findings support the fact that low-income individuals, which are the ones that likely are being benefited from the policy, switch from agriculture to the construction sector, which typically employs individuals with a low educational level. They also suggest something interesting: as the overall employment is increasing and emissions are decreasing, as described in Table 4, we can conclude that this substitution between agriculture and urban employment – which is associated with a structural transformation process – is driving the reduction in emissions. That is, the local activity of sectors with higher levels of emissions, such as agriculture, is being substituted by urban sectors that have lower levels of emissions.

Table 6: Treatment effects on employment, by sector

	Industry	Constr.	Trade	Services	Agriculture	Transp.
Treatment effect	0.099	0.247^{*}	-0.015	0.027	-0.049^{**}	-0.056
	(0.067)	(0.149)	(0.021)	(0.019)	(0.021)	(0.046)
Units	1981	976	2202	2324	2161	2212
Treated units	40	31	40	40	39	39
Groups	18	14	18	18	18	18

Notes: This table presents the estimates of the overall treatment effects, defined as in Equation (2), on the employment of different sectors. The columns indicate the sectors as defined in Table 1, which are, respectively, industry, construction, trade, services, agriculture, and transportation. The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021). Standard errors, clustered at the unit level, are presented in parentheses. Additionally, the table displays the total number of units used in the estimation, along with the number of treated units and treated groups. Significance levels are denoted as follows: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The dynamic treatment effects estimates for the sector employment outcomes are presented in Figure A.4 in the Appendix. Overall, none of the pre-treatment trends seem to be different between the treated and control groups.

7.1 Robustness

While the COVID-19 pandemic may have introduced unique dynamics in terms of emissions and employment across treated and control units, our analysis suggests that the treatment effects remained relatively stable during this period, as depicted in Figure A.2. Furthermore, the absence of significant mechanisms driven by car-to-bus substitutions, as indicated in Table 5, supports the notion that treated units would not respond too much differently during the pandemic years.

To bolster the robustness of our findings, we conducted an additional analysis by restricting the sample of emissions and employment to years prior to the COVID-19 pandemic. The overall treatment effects, presented in Table 7, remain consistent with absolute decoupling, with emissions being unaffected by the policy and employment exhibiting identical positive point estimates.

Table 7: Treatment effects on emissions and employment

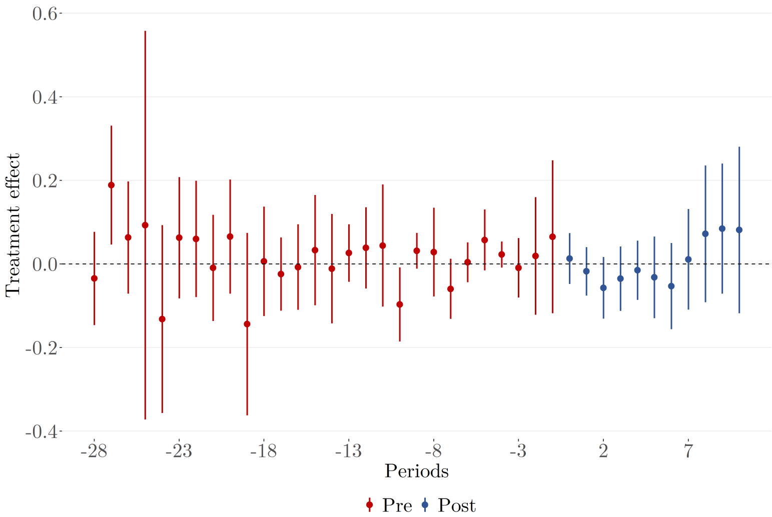
	GHG emissions	Employment
Treatment effect	0.004	0.038**
	(0.028)	(0.016)
Units	2204	2242
Treated units	26	26
Groups	17	17

Notes: This table presents the estimates of the overall treatment effects on emissions and employment, defined as in Equation (2). The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021), using a sample that is restricted to the pre pandemic years. Standard errors, clustered at the unit level, are presented in parentheses. Additionally, the table displays the total number of units used in the estimation, along with the number of treated units and treated groups. Significance levels are denoted as follows: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

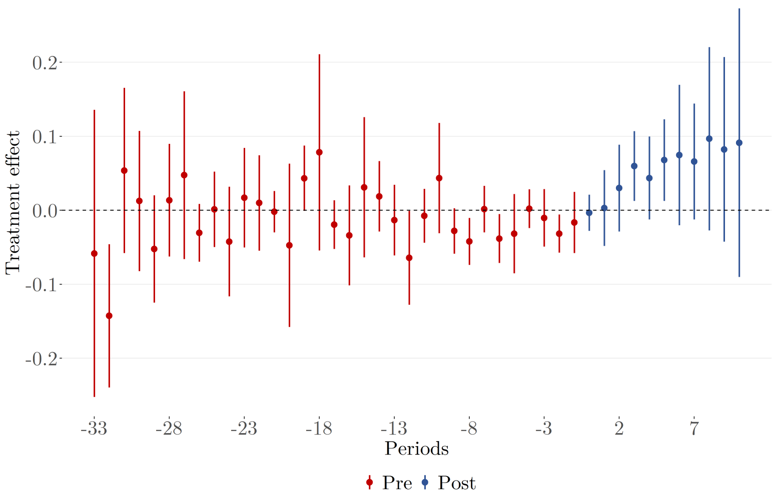
Furthermore, examining the dynamic treatment effects, as illustrated in Figure 6, reveals no evidence of differential pre-treatment trends between the treated and control groups for either outcome.

Figure 6: Heterogeneous treatment effects by length of exposure to the treatment for the pre pandemic sample

(a) Emissions



(b) Employment



Notes: This figure presents the estimates of the dynamic treatment effects from Equation (4), both pre and post treatment. Figure 3a presents the dynamic treatment effects on emissions, while Figure 3b presents the dynamic treatment effects on employment. The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021) using a varying base period and a sample restricted to the pre pandemic years. Vertical lines represent the 90% confidence intervals.

Additional figures detailing the heterogeneous treatment effects by group and year can be found in the Appendix (Figures A.1 and A.2). These figures demonstrate a consistent pattern akin to our baseline results, further corroborating the robustness of our findings across different subsets of the data.

8 Cost-benefit Analysis

To analyze the costs and benefits of the policy, we conduct a back-of-the-envelope calculation. The policy's cost can be estimated using urban transport expenses from the POF 2017-2018 dataset. The average annual expense for urban transportation in Brazil is BRL 123.48[15]. By applying this value to the annual population, we can ascertain the cost that local governments would need to finance to cover the entire fare for all users of the system within the municipality.

We have two types of direct benefits. The first one is a fiscal externality, stemming from the increase in the number of jobs, which will also raise the payroll level[16]. The second benefit is a reduction in carbon emissions, when valued by the social cost of carbon.

We employ the following procedure to calculate these two benefits:

1. For each treated municipality and each year after being treated, we add the estimated treatment effects from Table 4 to its respective observed outcome to retrieve the counterfactual outcome.

2. Then, we apply the exponential function to both the observed and counterfactual outcomes.

3. Finally, we compute the average of the observed and estimated outcomes, proceeding with the calculation of the difference of the averages to obtain the deviations in levels generated by the policy.

Let $\overline{\Delta E_t}$ denote the average reduction in greenhouse gas emissions, and $\overline{BC_t}$ denote the average benefit from the reduction in carbon emissions. Then, the formula for $\overline{BC_t}$ is given by:

$$\overline{BC_t} := SC_{2020} \times \varepsilon_{2020} \times \frac{P_{2021}}{P_{2020}} \times \overline{\Delta E_t} \tag{5}$$

[15] We assigned zero to individuals without urban transport expenses to avoid biasing the average upward.

[16] We estimated the treatment effects on the average wage of municipalities, and the results were not statistically significant. Thus, the increase in the number of jobs implies an increase in the payroll and taxes.

Here, SC_{2020} represents the social cost of carbon emissions in 2020 from US (2021)[17], ε_{2020} is the end-of-period exchange rate, and P_{2021} and P_{2020} are the IPCA values from 2021 and 2020, respectively.

In Brazil, employers are required to pay 20% of the payroll levels as taxes to the public pensions system. Direct taxes, including income taxes and public pensions system taxes, for employees vary based on their wage level. To determine the share of taxes with respect to labor income, we again utilize the POF 2017-2018 dataset[18]. We denote this value by τ.

Let $\overline{\Delta W_t}$ denote the average increase in payroll. Then, the average fiscal externality $\overline{F_t}$ can be defined as:

$$\overline{F_t} := (0.2 + \tau) \times \overline{\Delta W_t} \tag{6}$$

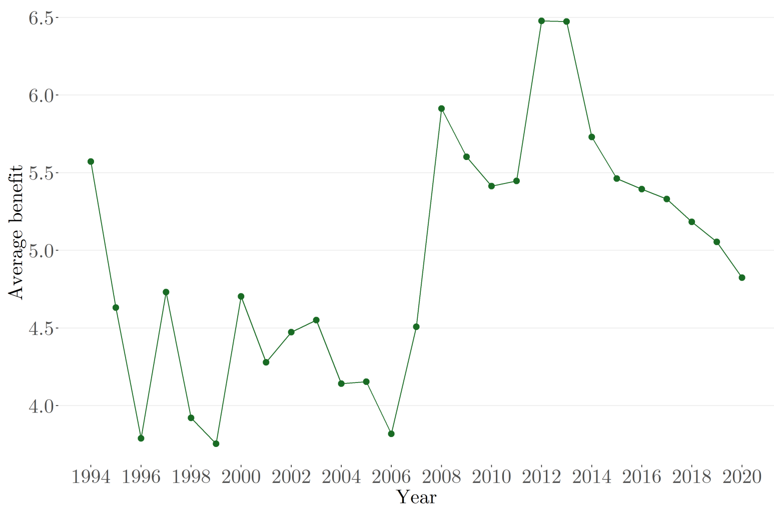
The total direct benefits will be the sum of (5) and (6). Figure 7 presents the average direct benefits of the policy by year.

[17] We use their average estimate with a 2.5% discount rate.

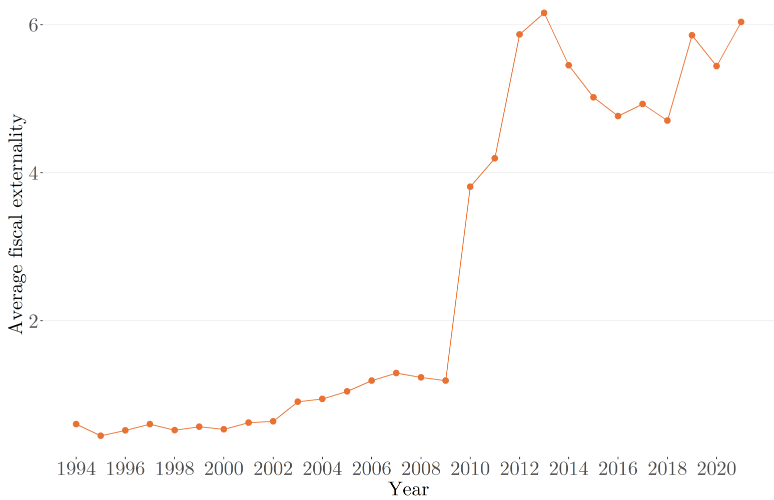
[18] By utilizing the labor income registry, it is possible to identify the labor income of each individual, the amount paid in labor income taxes, and the amount of taxes paid to the public pension system. Summing all the taxes and all the registries of labor income and dividing one by another yields the desired share.

Figure 7: Average direct benefits of the policy, by year

(a) Average benefit from reduction in carbon emissions



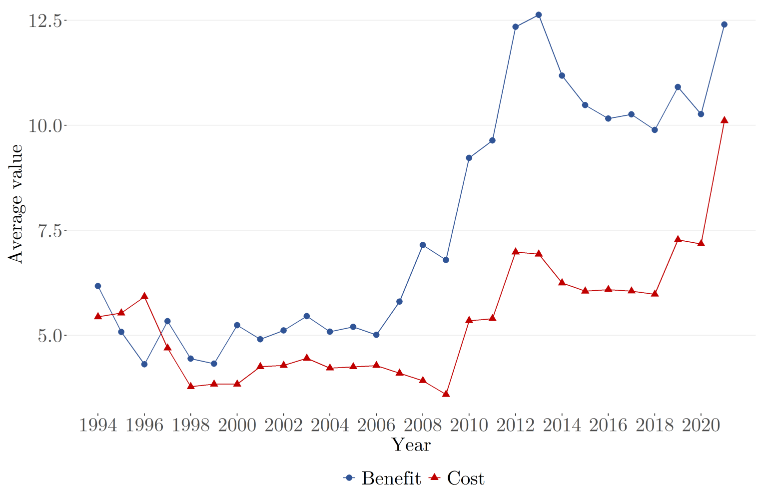
(b) Average fiscal externality



Notes: This figure presents the estimates for the two types of benefits of the policy. Figure 7a presents the estimates for the average monetary reduction of carbon emissions as defined in 5 and Figure 7b presents the estimates for the average fiscal externality as defined in Equation 6. The values are expressed in BRL millions.

Figure 8 summarizes the results above. Note that from 1997 onwards, the average direct benefit of the policy exceeds its costs for all years. This is an important finding, as we use a lower bound estimate for the fiscal externality: there are numerous other taxes associated with local economic activity that we have not considered in our analysis, such as taxes on services (*Imposto sobre Serviços*, or ISS) and flux of goods, services and transportation (*Imposto sobre Circulação de Mercadorias e Prestação de Serviços*, or ICMS).

Figure 8: Average cost and direct benefit of the policy, by year



Notes: This figure displays the average cost and direct benefit of the policy. The values are expressed in BRL millions.

9 Concluding Remarks

Climate change presents significant challenges for various economic indicators. Extensive literature has highlighted its impact on income, labor productivity, and shifts in economic activity. In response, nations have forged international agreements with explicit goals to reduce emissions while fostering sustainable growth.

Brazil stands out among nations committed to ambitious emission reduction targets. One policy recognized by the IPCC as potentially impactful is fare-free public transportation, already implemented in several Brazilian municipalities.

This study addresses this topic by examining the effects of adopting fare-free public transportation in Brazil, a vast and diverse country. Leveraging data from all instances of such policies across the nation, we employ a difference-in-differences approach within a staggered adoption framework. Our findings reveal that this policy leads to a reduction in greenhouse gas emissions in treated municipalities and stimulates local employment growth. These results support the notion that fare-free public transportation aligns with the goals of achieving absolute decoupling and sustainable economic development at the local level.

Furthermore, we investigate the mechanisms underlying these outcomes. Contrary to the expected shift from cars to buses, our analysis suggests a different pattern: a shift in employment composition, particularly from agriculture to urban sectors with lower emission levels. This finding echoes the work of Zárate (2022), highlighting how reduced commuting costs facilitate the inclusion of income-constrained individuals into the formal labor market, thereby increasing formal employment opportunities within cities.

We also conduct back-of-the-envelope calculations to examine the average costs and benefits of the policy. Our estimates indicate that the fiscal externality and the benefits associated with reduction in carbon emissions exceed the costs of the policy for the majority of the years.

This study aims to contribute to contribute to both Urban and Environmental Economics literature. Firstly, it utilizes novel Brazilian data to elucidate the impacts of an underexplored mitigation policy. Secondly, it contributes to the debate on commuting costs and employment dynamics, shedding light on structural transformations and shifts in employment composition. Finally, it estimates and discusses the the costs and benefits of the policy.

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Online Appendix to "Do Free Public Transport Impact Economic and Environmental Outcomes? Evidence from Brazil "

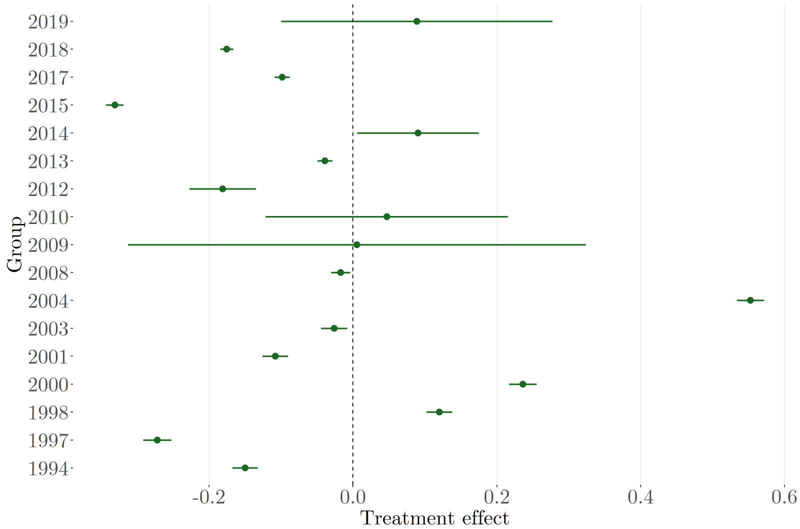
Mateus Rodrigues, Daniel da Mata and Vitor Possebom

July 22, 2024

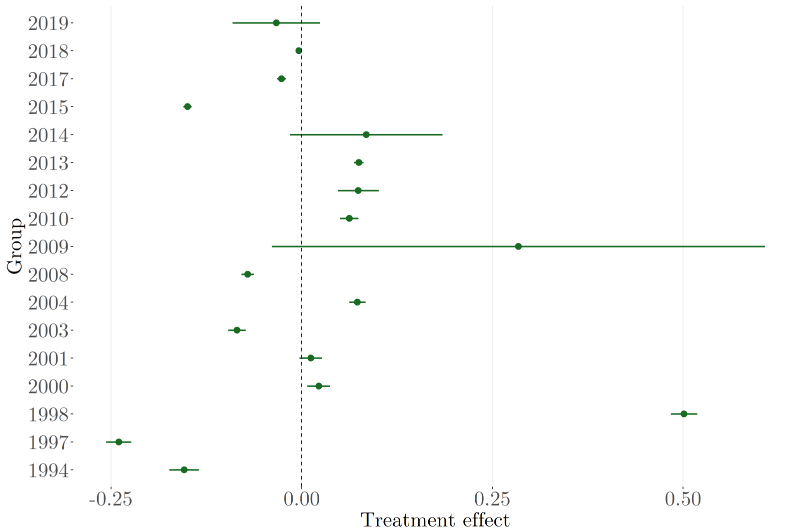
A Extra Tables and Figures

Figure A.1: Heterogeneous treatment effects by treatment group for the pre pandemic sample

(a) Emissions

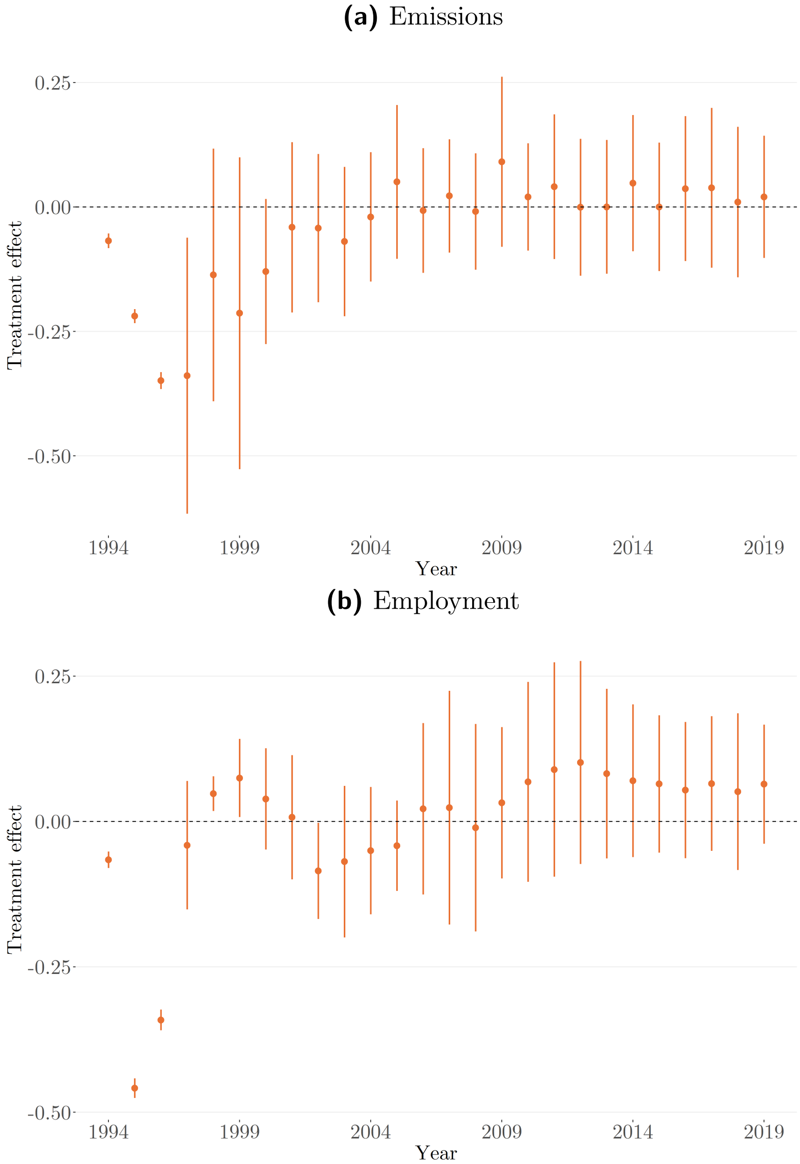


(b) Employment



Notes: This figure presents the estimates of the group treatment effects from Equation (1). Figure A.1a presents the group treatment effects on emissions, while Figure A.1b presents the dynamic treatment effects on employment. The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021) using a varying base period and a sample restricted to the pre pandemic years. Horizontal lines represent the 90% confidence intervals.

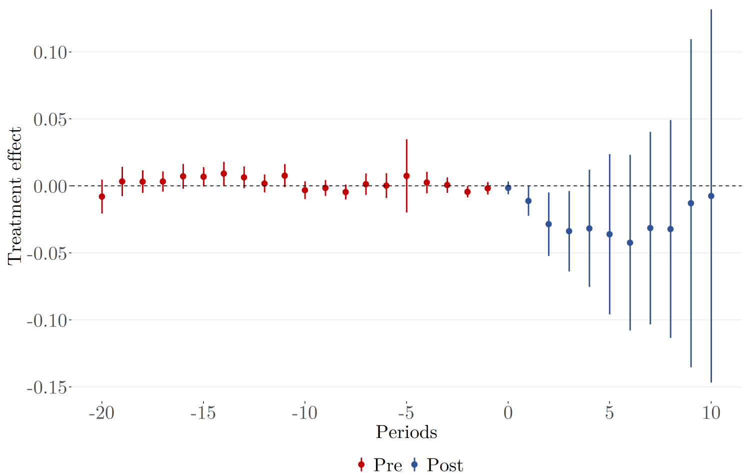
Figure A.2: Heterogeneous treatment effects by year for the pre pandemic sample



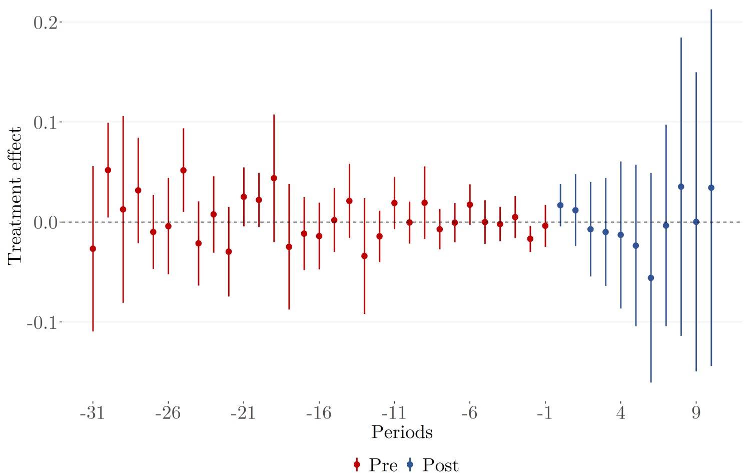
Notes: This figure presents the estimates of the treatment effects by calendar year from Equation (3). Figure A.2a presents the dynamic treatment effects on emissions, while Figure A.2b presents the dynamic treatment effects on employment. The estimation was conducted using the doubly-robust estimator proposed by Callaway and Sant'Anna (2021) using a varying base period. Vertical lines represent the 90% confidence intervals.

Figure A.3: Heterogeneous treatment effects by length of exposure to the treatment

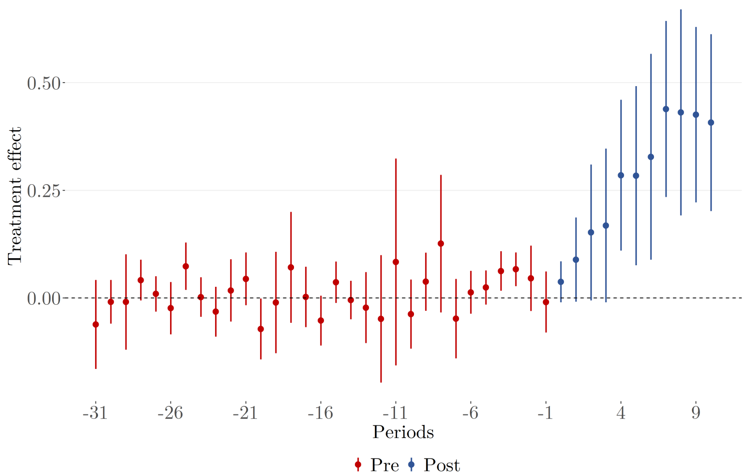
(a) Stock of cars



(b) Gasoline sales

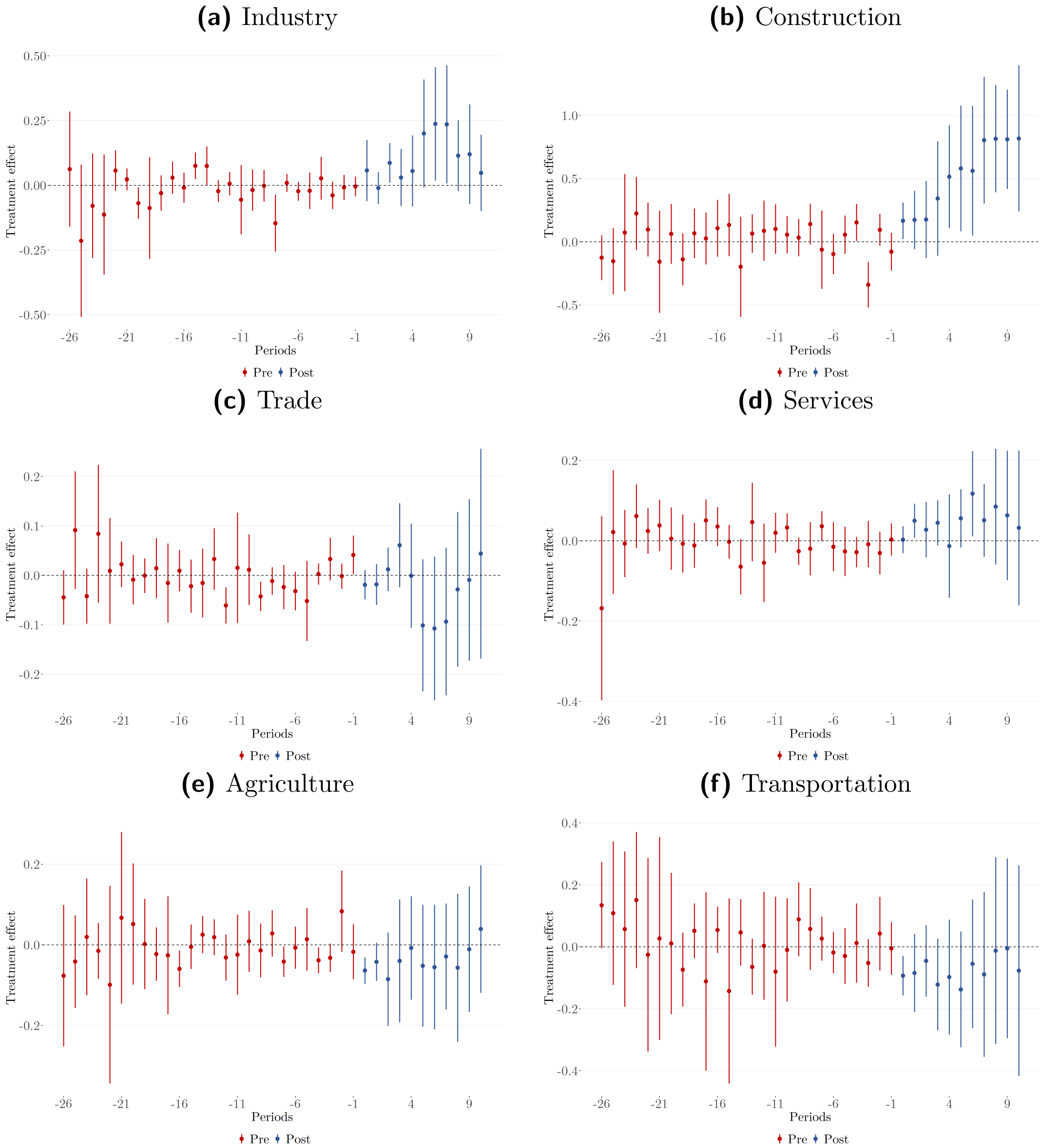


(c) Ethanol sales



Notes: This figure illustrates the estimates of the dynamic treatment effects from Equation (4), both pre and post-treatment. Figure A.3a presents the estimates for the stock of cars, Figure A.3b for the gasoline sales, and Figure A.4c for ethanol sales. The estimation employed the doubly-robust estimator proposed by Callaway and Sant'Anna (2021) using a varying base period. Vertical lines represent the 90% confidence intervals.

Figure A.4: Heterogeneous treatment effects on employment by length of exposure to the treatment, by sector



Notes: This figure illustrates the estimates of the dynamic treatment effects from Equation (4), both pre and post-treatment. All estimates pertain to the employment of the respective sector. Specifically, Figure A.4a presents the estimates for the industry sector, Figure A.4b for construction, Figure A.4c for trade, Figure A.4d for services, Figure A.4e for agriculture, and Figure A.4f for transportation. The estimation employed the doubly-robust estimator proposed by Callaway and Sant'Anna (2021) using a varying base period. Vertical lines represent the 90% confidence intervals.