Cash Transfers and The Environment*

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Preliminary version—Latest version available here.

Abstract

This article seeks to understand the role of cash transfers on the environment. For this, we used a policy change in the *Bolsa Família* Program (PBF) in 2009, which altered the number of beneficiaries and the monetary value of transfers between municipalities. We found a positive medium-run effect on Greenhouse Gases Emissions (GHG emissions) when comparing treated municipalities with their counterparts. However, this increase is not accompanied by an increase in the main emitting activities. We bring evidence of a general equilibrium effect of PBF using greater spatial refinement data. In this case, this effect would result from more circulation of money and people, so the increase in GHG emissions would be a by-product of economic activity.

JEL Classification: O12, Q51, Q56

Keywords: *Programa Bolsa Família* (PBF), Environment, GHG Emissions, Indirect Effect, Multiplier Effect

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1 Introduction

One of today's most significant and challenging problems is climate change. A broad mix of public policies must be discussed and implemented to tackle the arising threats (IPCC, 2014; Stern, 2008; Nordhaus, 2019). In Brazil, much empirical research has addressed concerns about the environmental public policies' direct consequences. There are plenty of examples: Assunção et al. (2013), and Ferreira (2021) seek to understand the monitoring effectiveness on deforestation, Assunção et al. (2020) explore the effect of rural credit, and Assunção et al. (2015) examine if the deforestation slow is due to environmental policies in action or agricultural prices. However, studies on the unintentional effect of other policies, which have nothing to do, a priori, with the environment, are rarer. Our objective is precisely helping to fill this gap by exploring the Programa Bolsa Família (PBF)[1], a Brazilian conditional cash transfer program. Meanwhile, to our knowledge, no study is looking at the possible environmental beneficial or harmful aftereffects. Furthermore, the literature on this topic is incipient.

Several papers have proposed a functional relationship between environmental quality and income per capita (Grossman and Krueger, 1995; Selden and Song, 1994; Holtz-Eakin and Selden, 1995; Kaufmann et al., 1998). These papers rely on the idea of an inverted-U relationship; that is, there is a turning point at which higher income is associated with better environmental quality. This relationship is known as Environmental Kuznets Curve. In this relationship, the PBF context would be located in the curve's initial part. More recent studies show the functional form is not that simple (Azomahou et al., 2006; Stern, 2017), turning to an ambiguous question. This debate contributes to the discussion between poverty alleviation, economic growth, and the environment and it requires more empirical evidence.

Castañeda et al. (2018) reports that most low-income families live in impoverished areas and depend on environmental goods. Hubacek et al. (2017) argues that moving people from extreme poverty does not significantly impact emissions, meanwhile forcing people to a modest income level would have a considerable effect. Cash transfers' impact, however, can be positive or negative, or more specifically, associated with emitting activities, such as deforestation (carbonizing factors), or production changes that alleviate the emission process, such as shifting from livestock to crops (decarbonizing factors) (Da Mata and Dotta, 2021). This result will depend on the economic particularities of the region under analysis. These possible outcomes caused by poverty

[1] Much is known about the direct impact of the PBF. By direct effect, we refer to impacts on variables intrinsically incorporated into PBF, such as spending via increased income or education and health via conditionality imposed by the program. Some studies evaluate the spillover effects on fertility rates, elections, and other dimensions. See Ribeiro et al. (2017) for an extensive literature revision about the PBF program and its consequences.

alleviation can be explained by (Alix-Garcia et al., 2013): (i) there may be an increase in the demand for goods that are resource intensive so that there is a deterioration in the quality of the environment; (ii) there may be an increase the demand for environmental resources and/or an increase in the opportunity cost for extractive activities so that there is an improvement in the quality of the environment. These two possibilities indicate that the sign of the effect can make the PBF an auxiliary tool for environmental public policies or a program that can generate some concern regarding its decarbonizing aspect.

The evidence is diverse. Some studies find a carbonizing effect, whether using deforestation as an environmental quality index (Zwane, 2007; Alix-Garcia et al., 2013) or with other measures related to pollution (Behrer, 2023). If the cash transfer is conditional on protecting the environment, positive results can be observed (Jayachandran et al., 2017). These results go against the result found by Ferraro and Simorangkir (2020). A possible mechanism would be the facilitation of migrating. The departure of people may have eased the deforestation process. Not necessarily this case, more income would alleviate deforestation because it would increase the demand for forest products more than the increase in the demand for farming products (Foster and Rosenzweig, 2003). Of greatest consensus is the increase in the consumption of potentially emitting products (Hanna and Oliva, 2015; Gertler et al., 2016; Haushofer and Shapiro, 2016). Nevertheless, this increase is not necessarily accompanied by deforestation (Malerba, 2020).

Using a Dynamic Difference-in-Differences design and exploring a policy change in PBF, we show an increase in GHG emissions of about 5%[2] when comparing the treated municipalities against the non-treated. However, the main result is not driven by the rise in deforestation or the increase in pasture/farming areas and production, both central components of total emissions in Brazil. Reinforcing this point, there is no impact on the probability of fires, showing no difference in behavior between groups regarding soil change. Though, there is an impact on fines, with an effect pattern similar to GHG emissions, suggesting that part of these emissions result from illegal activities. All these show that the increase in emissions is not coming from a specific activity. This feature may result from a general equilibrium effect of *Bolsa Família*, which altered the behavior pattern of beneficiaries regarding mobility, consumption, and investment.

Cash transfer functioning as a general equilibrium tool is well documented in the literature (Gerard et al., 2021; Egger et al., 2022). Our notion of the general equilibrium effect has a geographic appeal: the environmental degradation (generated by

[2] In 2008, the year before the change, GHG emissions from treated municipalities were 25% higher than those from municipalities in the control group.

the carbonizing effect) is not a direct result of the beneficiary and, therefore, does not happen in the beneficiary's home region. If there is no distinction between the region where the beneficiary lives and the regions further away from his/her residence, then there would be evidence of a general equilibrium effect so that the cash transfer recipient is not directly responsible for environmental degradation. For example, this result would be explained by the circulation of money and people, where more money would generate greater demand and consumption, creating a chain reaction. We will call this effect the local multiplier effect or, simply, the indirect effect (be careful not to confuse it with the direct effect of the conditionalities of the program), and we present suggestive evidence about it. In this sense, the increase in GHG emissions would be a residue of economic development.

Our work contributes primarily in three ways. First, we present evidence of the unintended impact of a cash transfer policy on the environment, studying the heterogeneous effects caused by the program change. This will be essential to understand how municipalities are differently affected and the mechanisms behind the main result. As a second contribution, we estimate medium-term effects on greenhouse gases, a variable slightly used in the literature. The most common proxy for environmental quality is the level of deforestation. Finally, even if suggestively, we present that the mechanism responsible for the increase in emissions comes from a general equilibrium characteristic of the PBF. This multiplier effect would be the result of a response of economic activity in relation to the benefit of the program.

The rest of the paper is organized as follows. Section 2 discusses the institutional aspects of the *Bolsa Familia* program. Next, Section 3 presents the main empirical strategy based on the PBF policy change, whose unit of analysis is the municipality. Section 4 lists all the data sources. Section 5 presents the results for GHG emissions and their potential mechanisms using the main empirical strategy. Section 6 refers to the heterogeneity caused by the change in the program, so municipalities are affected differently by the policy. Section 7 addresses, using data with a more refined granularity than the municipality, on the problem of the local multiplier effect, bringing suggestive evidence that the main result of GHG emissions is the result of a general equilibrium effect of *Bolsa Família*. Section 8 exposes a series of robustness tests, whether about constructing the treatment variable of the main empirical strategy or making inferences. Finally, Section 9 concludes and discusses some limitations and potential next steps.

2 Institutional Context

The *Programa Bolsa Família* (PBF) is the world's most extensive conditional cash transfer program (Rasella et al., 2013). It began in October 2003, from the combination of several national social programs (Soares and Sátyro, 2009). For a family to be part of the program, it necessarily needs to be registered in *Cadastro Único* (*CadÚnico*)[3] and fulfill the income restrictions imposed by the program. *CadÚnico* contains not only the PBF beneficiaries but families with monthly income below half of the minimum wage (a family can be in *CadÚnico* since the registration is linked to social programs). Furthermore, the income restrictions impose that the monthly family income per capita needs to be below R$154, 00 (in 2015 values – the monthly value of the minimum wage in 2015 is R$788, 00). The PBF has two essential features[4]. The first one is also the most known: conditionalities. Two options arise:

- If the monthly per capita income is below R$154, 00 and greater than R$77, 00, then the family receives only the variable benefit (pregnant women, nursing mothers, children and teenagers up to 15 years old – one family can accumulate up to 5 benefits). These families are classified as poor. The value of the benefit is R$35, 00. Furthermore, families that receive conditionalities must accept certain requirements, such as high school attendance by children and an up-to-date vaccination schedule. Therefore, the direct effects of the program are related to these established requirements;

- If the monthly per capita income is below R$77, 00, then the family is classified as extremely poor. In this case, the family receives the basic benefit plus conditionalities, if applicable. The value of the benefit is R$77, 00.

There are also two other benefits. The family has a specific advantage if a family has teenagers (16 or 17 years old). Finally, if a family, regarding all the cash transfers received, is still classified as extremely poor, then the government completes the value so that the monthly per capita income is R$77, 00.

The second PBF feature is the definition of a national quota and, consequently, the distribution of this quota to municipalities. To have a policy of targeting the neediest municipalities, the federal government estimates the number of low-income families in each city. The estimate defines the number of families that should receive the benefit. Even if the family is eligible to be part of the program, participation is not guaranteed: the municipality needs to have an available slot. Barros et al. (2008) highlights the

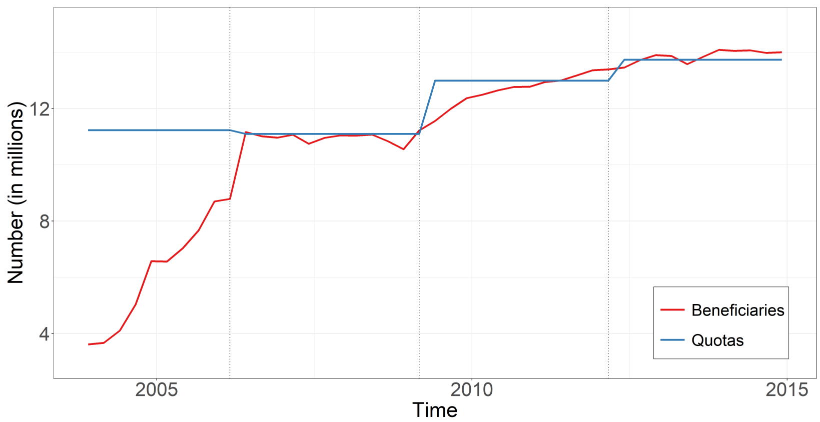
[3] *CadÚnico* is a database managed by the Brazilian government that catalogs the most vulnerable families. The objective is to use this as a tool to implement public policies.

[4] From *Ministério do Desenvolvimento Social* (Ministry of Social Development).

importance of the target system. The quota definition is not a strict rule, but it is crucial for defining the number of beneficiaries.

The quota was initiated in 2003 with the PBF start. Until 2012, the number of allocations was revised every three years. In 2009, there was a change in the methodology. This change was responsible for altering the percentage of the national slot destined for each municipality. Also, this year, there was an attempt to expand the benefit for more families. All these components will be more precise in the next section, where we discuss the empirical strategy used. Figure 1 below presents the evolution of the number of quotas and beneficiaries over time.

Figure 1: Number of Quotas and Beneficiaries Over Time



Notes: Evolution of the number of quotas (blue line) and the number of beneficiaries (red line) over time. The PBF began at the end of 2003. The quota was revised in April 2006, May 2009, and May 2012. The dashed lines represent these revisions. The middle line, from May 2009, marks the date of introduction of the new quota, calculated using a new methodology.

At the beginning of 2004, the difference between the number of quotas and the number of beneficiaries is enormous because, naturally, the program has only started. This difference declines over time. At some point before 2009, the difference is negligible. In May 2009, there was a change in the quota calculation methodology. This change was responsible for distributing the national slot between the municipalities differently. As already said, there was an attempt too to expand the PBF. That is why there is a "jump" in quotas. After that, the number of beneficiaries also grows, becoming even more significant than the number of beneficiaries (evidence that the quotas are not a strict rule). However, the number of PBF beneficiaries seems constantly influenced by the number of allotments. The following section provides information on how the allocations were calculated. We will explore this change from 2009.

3 Main Empirical Strategy

In this section, we follow Gerard et al. (2021) for constructing the treatment variable. As mentioned in Figure 1, there were two quotas quantities before the change in methodology in 2009. In 2003, the quota distribution followed the rule:

$$Quota_m^{2003} = \frac{Poor_{ms}^{2000}}{\sum_{k \in s} Poor_{ks}^{2000}} \times Poor_s^{2001} \tag{1}$$

$Poor_s^{2001}$ represents the total number of poor families in the state s and year 2001, calculated by PNAD[5]. $Poor_{ms}^{2000}$ represents the total number of low-income families in the municipality m and state s in 2000, calculated by Census[6]. Notice that PNAD only defines the total slot by state. Consequently, the national slot is defined as summing all the states. Therefore, the Census is important for distributing quotas across municipalities (PNAD does not have differentiation by municipality). Note that the municipal quota is an estimate of the number of poor families in the municipality. In 2006, the quota was calculated as follows:

$$Quota_m^{2006} = \frac{Poor_{ms}^{2000} \cdot n_{ms}^{[2000,2003]}}{\sum_{k \in s} \left(Poor_{ks}^{2000} \cdot n_{ks}^{[2000,2003]} \right)} \times Poor_s^{2004} \tag{2}$$

The methodology is the same as in (1), with slight differences in the data sources. First, there is an update in PNAD for slots calculation across states. Finally, the term $n_{ms}^{[2000,2003]}$, measured by the *Instituto Brasileiro de Geografia e Estatística (IBGE)*, represents the population growth between 2000 and 2003 in the municipality m of state s. Multiplying the number of low-income families calculated by the Census by the population growth accounts for the change in the number of low-income families in each city. This population growth term is necessary because there was no new Census survey until 2010, while PNAD is held annually (except in the Census year). Note that there is an implicit assumption: the growth in the number of households equals the population growth.

In 2009, however, the distribution of slots across municipalities was altered. The allocation was made according to the following:

$$Quota_m^{2009} = \frac{\widehat{Poor}_{ms}^{2006}}{\sum_{k \in s} \widehat{Poor}_{ks}^{2006}} \times 1.18 \times Poor_s^{2006} \tag{3}$$

Naturally, there is an update in the PNAD (in this case, using data for the year

[5] Gerard et al. (2021): the number of low-income families is calculated according to the "half of the minimum wage per capita"

[6] Gerard et al. (2021): the number of low-income families is calculated according to the "total income below twice the minimum wage."

2006). The term 1.18 is, as already mentioned, the attempt to expand the PBF. There is a long discussion on how vulnerability can not be only determined by income (Soares, 2009). Lastly, the apportionment is no longer done by the Census calculation of low-income families. Now it is done using a prediction model. This new method is responsible for changing the allocation percentages across municipalities. So, it is possible to define a counterfactual quota, i.e., the municipality quota in the event that no methodology change has been made. In this case, also accounting for the expansion of the program, so that the only change is the allocation fraction, the counterfactual quota can be defined as:

$$CountQuota_m^{2009} := \frac{Poor_{ms}^{2000} \cdot n_{ms}^{[2000,2006]}}{\sum_{k \in s} \left(Poor_{ks}^{2000} \cdot n_{ks}^{[2000,2006]} \right)} \times 1.18 \times Poor_s^{2006} \tag{4}$$

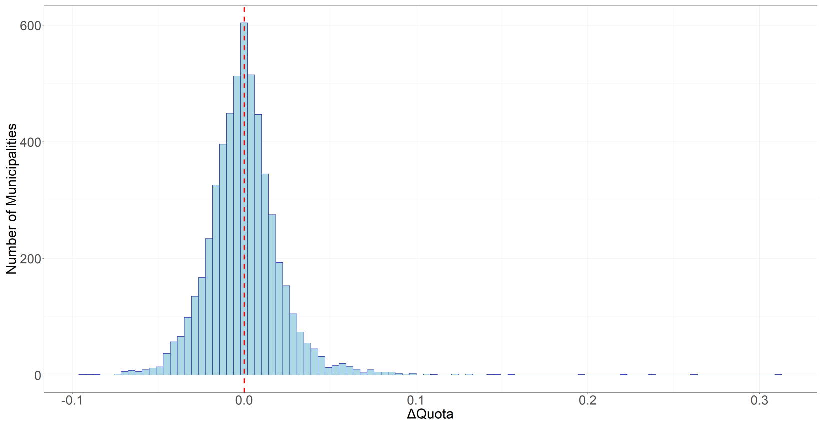
The expression above represents the quota per municipality in 2009 in a scenario where the 2000 Census still does the allocation across cities. Finally, define the following quantity:

$$\Delta Quota_m := \frac{Quota_m^{2009} - CountQuota_m^{2009}}{Pop_m^{2006}} \tag{5}$$

The term Pop_m^{2006} represents the total population in municipality m, putting all cities in a "common measure". In Section 8, we will define different forms for $\Delta Quota_m$ and show that the results remain the same.

Figure 2 shows the main variable distribution. The median is approximately zero. Municipalities above the median are municipalities with more actual quota than would be if the methodology has not changed. In contrast, municipalities below the median have less actual quota than would if the methodology had not changed.

Figure 2: $\Delta Quota_m$ Distribution



Notes: The median is approximately zero. The distribution is almost symmetric, with some more discrepant elements in the right tail.

Our benchmark specification of interest is the Dynamic Difference-in-Differences approach as follows:

$$y_{mt} = \phi_m + \theta_t + \sum_{\lambda \neq 2008} \beta_\lambda \times \mathbb{1}_{\{t=\lambda\}} \times Treat_m + \\ + \sum_k \sum_{\lambda \neq 2008} \gamma_{\lambda k} \times \mathbb{1}_{\{t=\lambda\}} \times x_m^k + \varepsilon_{mt} \tag{6}$$

where $Treat_m$ is either a binary variable, receiving one if $\Delta Quota_m$ is greater than the median of the distribution, or a continuous variable, i.e., $Treat_m := \Delta Quota_m$. y_m is the dependent variable, representing GHG emissions (in the log) in the main regression. ϕ_m and θ_t are municipality and year fixed effects, respectively. x_m^k are municipality-level controls that include the labor force, the proportion of men, GDP, the aging rate, and the initial quota (which was defined before PBF implementation). The first four controls are from the 2000 Census. The last one, the initial quota, was determined using the 2000 Census and PNAD 2001. The main hypothesis is parallel trends. We are interested in the β_λ parameters; 2008 is the omitted coefficient, one year before the methodology change. The error term is clustered at the municipality level. In Section 8, as robustness checks, we will change this cluster level, clustering at the microregion level and doing Conley regressions to account for spatial correlation. In almost all regressions, the initial analysis year is 2003, and the final year is 2015 (the quota update was 2012). As explained in Section 1, the effect can be positive or negative, depending on the relative strength of carbonizing and decarbonizing factors.

4 Data

This section summarizes all the data sources used in the main empirical specification. As already mentioned, the sampling unit is the municipality. Also, we briefly indicate the data sources necessary for the local multiplier effect approach.

Number of PBF beneficiaries and monetary value of the transfers:[7]. Since the start of the program, we have had access to the number of beneficiaries, the total amount of transfers by the municipality, and the values of municipal quotas. Previous graphs were produced using this source.

GHG Emissions: from *Sistema de Estimativas de Emissões e Remoções de Gases de Efeito Estufa* (SEEG) – *Observatório do Clima*. From information on economic activities, it is possible to quantify the total emissions by the municipality. There are different greenhouse gases (carbon dioxide (CO_2), methane (CH_4), and others), so they present the data in a standard metric (an equivalent carbon metric). A survey of activities and mapping of each component responsible for gas emissions are carried out. We use gross emissions, where carbon dioxide removal is not accounted for. It is possible to obtain the total GHG emissions at the county level (however, there is no information for a finer granularity). De Azevedo et al. (2018) explains in detail the calculation methodology used. We use the latest version available.

Deforestation: PRODES, from Instituto Nacional de Pesquisa Espacial (Inpe), performs the Amazon forest monitoring using satellite images. The satellite has a 20 to 30m spatial resolution. This generates a highly accurate precision on the deforestation area. Deforestation rates are, therefore, how much was deforested in each pixel. With this, generating the total deforestation in a given municipality is possible.

Deforestation alerts: data bringing information about threats to Amazon forest cover, from Degrad/DETER (Inpe). The satellite accuracy is less efficient than the PRODES satellite. However, this data source helps government monitoring throughout the year, being a tool primarily aimed at monitoring. Detection classes are deforestation, degradation, and logging. This data and PRODES are, naturally, a subsample from Brazil.

Fines: the entity responsible for imposing fines is the Ibama, an agency responsible for environmental inspection and punishment. This information is publicly available and allows us to know whether a penalty was applied in a municipality. Also, there is information about the fine's latitude and longitude. This granularity will be important in the analysis of the local multiplier effect.

[7] All the information about the PBF is from *Lei de Acesso à Informação (LAI)*, which gives the right of access to public information

Land Cover and Land Use: MapBiomas provides information on how the land is organized in Brazil using 30m×30m pixels images. This means it is possible to disentangle the country into areas such as cities, pasturage, farming, forest, and other types. This allows us to understand the transitions that occurred in the land. We use the latest version available.

Farming and Livestock: *Pesquisa Agrícola Municipal (PAM)* and *Pesquisa Pecuária Municipal (PPM)*, from *Instituto Brasileiro de Geografia e Estatística (IBGE)*, are surveys that seek to quantify the agricultural production in the country. The farming area is provided by *PAM*, and the number of heads of cattle is provided by *PPM*.

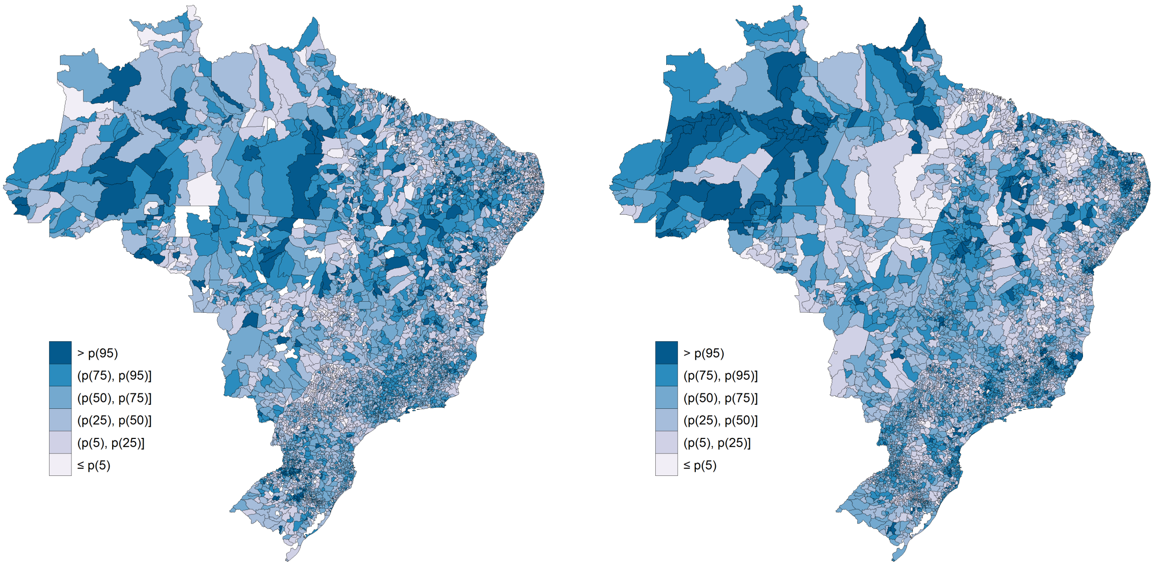
Fires: *Banco de Dados de Queimadas* (BDQueimadas)/Inpe provides, via satellite image, the location of fires. This makes it possible to know fire occurrence in a given municipality.

All bases have a start date in 2003, except for fines (2005) and deforestation alerts (2007). For all regressions, there are $5,507$ municipalities[8] for each year, except for the deforestation datasets (745 for PRODES and 609 for DETER). As an illustration, Figure 3 below shows more or less some correlation between the treatment variable (defined by equation (5)) and GHG emissions. Panel (a) and Panel (b) illustrate the $\Delta Quota_m$ and the percentage variation in emission between 2008 (the first year before the methodology change) and 2015 (the last year of analysis), respectively. Also, Appendix A shows the correlations between GHG emissions and the number of beneficiaries in 2012, some time after introducing the new calculation policy. It is possible to notice a positive correlation between the variables, giving evidence that the effect we will find with the main strategy is also positive.

As mentioned, the 2000 Census and PNAD 2001 were used to construct the controls for the main specification. Also, as will be better explained in Section 7, which deals with the local multiplier effect, we used the 2010 Census Universe and 2010 Sample Census. The 2010 Census allows us to construct variables of interest at the municipality level. With the Census Universe, it is possible to build statistics with greater detailing appropriate for the PBF general equilibrium analysis. Finally, we used a vulnerability classification performed by IPEA (*Instituto de Pesquisa Econômica Aplicada*). However, this classification makes full use of the 2010 Census data.

[8] Number of municipalities in 2000

Figure 3: $\Delta Quota_m$ and GHG Emissions Maps



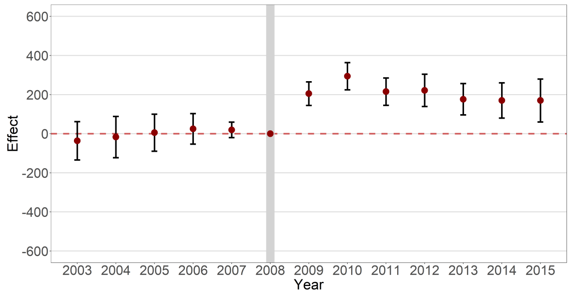
(a) $\Delta Quota_m$ **(b)** Emission variation (2008–2015)

Notes: Panel (a) represents the treatment variable across municipalities. Panel (b) represents the relative change in GHG emissions between 2008 (one year before the PBF modification) and 2015 (the final year of analysis). $p(.)$ represents the percentile of the variable under analysis.

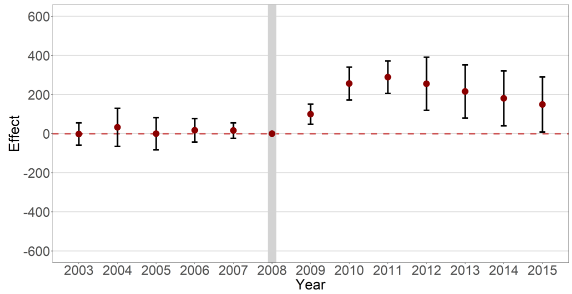
5 Results

First, we present the results related to the *Bolsa Família* program. It is important to show that the change in methodology generated changes in the number of beneficiaries and, consequently, in the monetary amount originating from the program when we compare the treated municipalities with the untreated ones. Figure 4 shows the results for the number of PBF beneficiaries and the total amount of money, using the binary treatment variable (receives 1 if $\Delta Quota_m$ is above the median). These results support the parallel trends assumption.

Figure 4: PBF Results with the Binary Measure



(a) Number of PBF beneficiaries

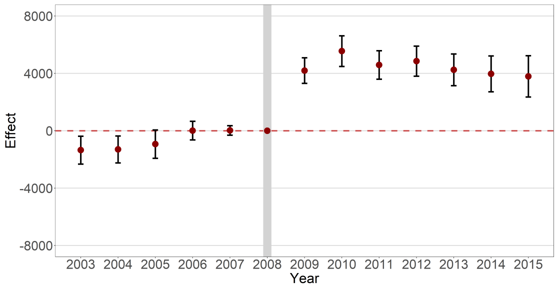


(b) Monetary Value (in thousands)

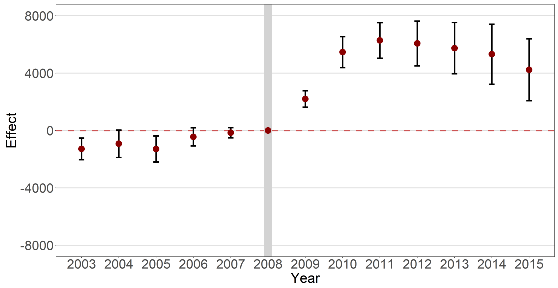
Notes: This figure shows the effect of the PBF methodology change in the number of PBF beneficiaries and the monetary value of the PBF transfers (in thousands), using the binary treatment measure and 95% confidence intervals. Panel (a) represents the effect on the number of PBF beneficiaries. The average number of beneficiaries in 2008 was 1913. Panel (b) represents the effect on the monetary value of the PBF transfers. All values deflated to 2010. The average total monetary value in 2008 was R$2,123,529.

For the number of PBF beneficiaries, the results suggest an increase of approximately 200 beneficiaries when comparing treated municipalities to non-treated municipalities. The average number of beneficiaries in the period just before the policy change is 1913. For the monetary value of the transfers, the results suggest an increase of approximately R$200,000, with all values deflated to 2010. The average transfer money in 2008 was R$2,123,529. The change in the calculation of quotas was responsible for more beneficiaries and, consequently, more money distributed. Transforming this quantity to monthly values is almost the values discussed in Section 2. Similar results can be shown in Figure 5 using the continuous treatment variables (the own $\Delta Quota_m$ measure), despite a more salient pre-trend. It is possible to interpret these results through a change from 0 to 0.01 in the $\Delta Quota_m$. This is the same as moving from the median to the third quartile. This generates almost 60 more beneficiaries and R$60,000 in money.

Figure 5: PBF Results with the Continuous Measure



(a) Number of PBF beneficiaries



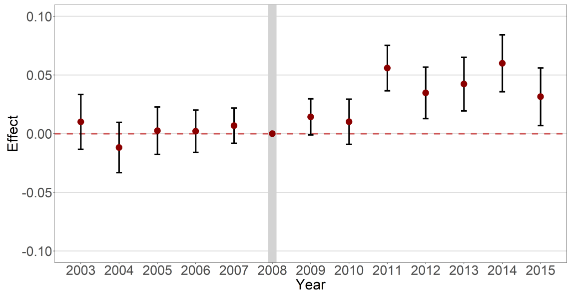
(b) Monetary Value (in thousands)

Notes: This figure shows the effect of the PBF methodology change in the number of PBF beneficiaries and the monetary value of the PBF transfers (in thousands), using the continuous treatment measure and 95% confidence intervals. Panel (a) represents the effect on the number of PBF beneficiaries. The average number of beneficiaries in 2008 was 1913. Panel (b) represents the effect on the monetary value of the PBF transfers. All values deflated to 2010. The average total monetary value in 2008 was R$2,123,529.

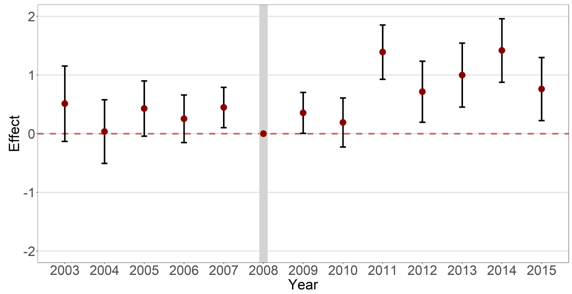
Figure 6 shows the results for our variable of interest, GHG emissions, in the natural logarithm transformation. We conclude a 5% increase in GHG emissions with the binary measure, comparing treated units to the control units. The increment of beneficiaries in these municipalities most probably drives this result. With the continuous measure, we still see an increase, in this case, slightly bigger than 1% when moving from $\Delta Quota_m = 0$ to $\Delta Quota_m = 0.01$.

Note that these results have a certain delay. Two possible reasons are: (i) people with new money need to rearrange themselves in economic terms, generating a delay for a new pattern of consumption/activities, and/or (ii) the methodology change was in mid-2009, so new beneficiaries entered the program only at the end of 2009 or mid-2010. Note that the point estimate for 2009 in the regressions that address the number of beneficiaries and the monetary value of transfers is lower than the point estimates for subsequent years. Also, in 2015 the estimate decreased. This may happen because, near 2015, the estimate for PBF beneficiaries and monetary value decreased too. Hence, the dynamic of GHG emissions seems to be guided by the dynamics of the program.

Figure 6: GHG Emissions Results



(a) GHG emissions (binary treatment)



(b) GHG emissions (continuous treatment)

Notes: This figure shows the impact of the PBF methodology change on GHG emissions (in the log), with 95% confidence intervals. Panel (a) represents the effect on GHG emissions using the binary treatment variable. Panel (b) also represents the effect on GHG emissions but uses the continuous treatment variable.

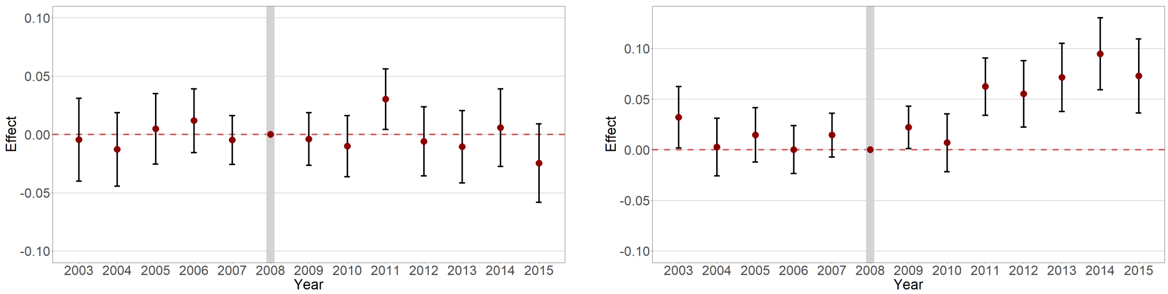
Not surprisingly, the probability of fines increases. This means some GHG emissions come from illegal activities (see Figure B.1a). This result will be relevant in future analyses. Besides economic activity in general, some of the driving forces of GHG emissions are deforestation and pasture. However, we do not see an effect on deforestation, cultivation, pastoral areas, or livestock production. The PBF does not affect deforestation, even using the PRODES satellite database (Figure B.1b), the deforestation alerts generated by DETER (a measure that assists in detecting illegal activities – Figures B.1c), and forest cover via MapBiomas data (Figures B.1d). Results from different sources indicate the same direction, supporting the idea that the channel of GHG emissions rise is not the deforestation process. Furthermore, we do not see an impact on agriculture, even using the farming area provided by PAM (Figure B.1e), the heads of cattle offered by PPM (Figure B.1f), and the ground cover intended for agricultural areas (Figure B.1g), data originating from the work of MapBiomas. Again, different sources bring the same story: increase in the productive area and/or intensification of production do not seem to be the mechanisms responsible for the increase in emissions when comparing municipalities with $\Delta Quota_m > 0$ against municipalities with $\Delta Quota_m < 0$. Also, there is no effect on the probability of fires, representing no more attempt to transform the ground (Figure B.1h). Similar results can be found even using the continuous treatment measure ($Treat_m = \Delta Quota_m$). See Figure B.2.

This means that the GHG emissions are not coming from these activities, bringing for the first time evidence that the effect is due to economic activity (our notion of local multiplier effect or indirect effect). In this sense, the cash transfer recipients are not directly responsible for the emissions. This might happen because the *Bolsa*

Família alters the consumption pattern, i.e., the cash transfers can change the amount consumed and modify the accessible markets. Such a channel is well documented in the literature (Ribeiro et al., 2017). On this hand, it is possible to think of the increase in emissions as a residue of boosted economic activity, driven by the multiplier effect of money, which generates greater market accessibility for beneficiaries, which in turn changes the way of production in the local economy. We might bring evidence about the multiplier effect. First, it is necessary to explore program heterogeneity since the change in calculation methodology somehow impacts all municipalities. By understanding how the cities are differently affected, it will be possible to test whether this carbonizing result comes from an indirect effect.

An auxiliary result to this dynamic would be to test whether the effect comes from denser cities. Figure 7 presents the results for GHG emissions separated by its median value. We see a positive and significant impact for denser municipalities, while this effect does not occur in the less dense municipalities.

Figure 7: GHG Emissions Results by Population Density



(a) GHG emissions (binary treatment) **(b)** GHG emissions (continuous treatment)

Notes: This figure shows the impact of the PBF methodology change on GHG emissions (in the log), with 95% confidence intervals. Panel (a) represents the effect on GHG emissions for municipalities below the density median. Panel (b) also represents the effect on GHG emissions but only for municipalities above the density median..

Also, we present the results for GHG emissions separated by biome. We can see a predominant effect coming from Mata Atlântica. This biome covers the east coast of Brazil, which includes most of the country's main municipalities. Although the mechanisms do not indicate (or indicate weakly), the effect in the Amazon is strong, even if not statistically significant. This suggests that there is a gap in better understanding.

Table 1: GHG Emissions Results by Biome

Model:	(1) Amazônia	(2) Caatinga	(3) Cerrado	(4) Mata Atlântica	(5) Pampa
Effect	0.0550	-0.0293*	0.0107	0.0368***	-0.0003
	(0.0364)	(0.0176)	(0.0156)	(0.0096)	(0.0240)
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	7,085	15,678	18,382	39,533	2,795
R^2	0.9228	0.9219	0.9573	0.9441	0.9819
Within R^2	0.0979	0.0356	0.0474	0.0152	0.0571

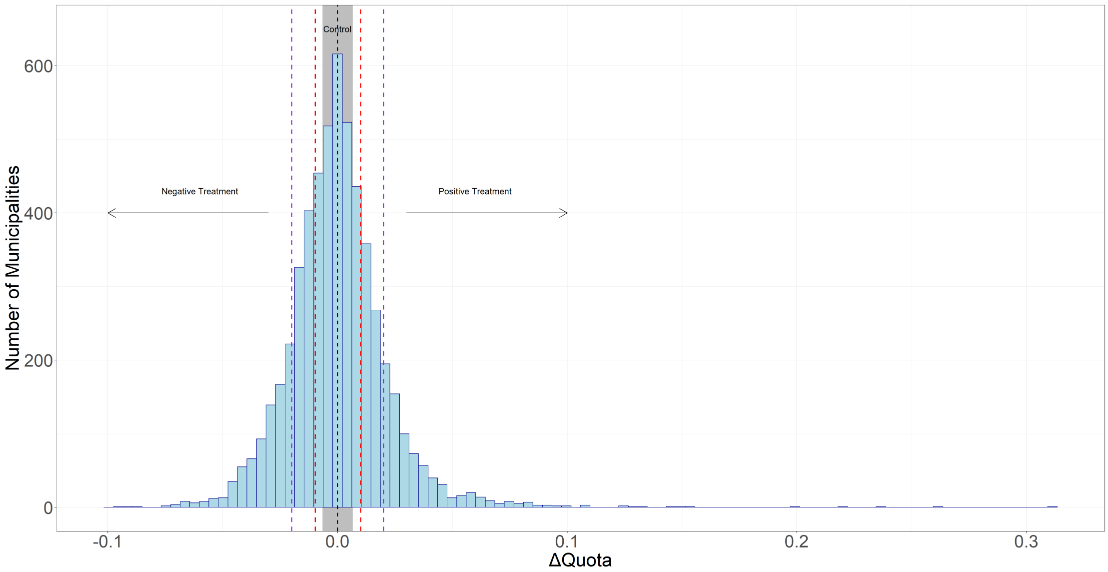
Clustered standard-errors in parentheses at the municipality level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

6 Heterogeneity Analysis

As shown in Figure 2, many municipalities have faced essential changes in the $\Delta Quota_m$ variable, while others have the $\Delta Quota_m$ value near zero. This can be viewed as three different scenarios: (i) some municipalities have less quota than they would have if the methodology did not change (municipalities with $\Delta Quota_m$ negative, but somehow far from zero), (ii) some municipalities have more quota than they would have if the methodology did not change (municipalities with $\Delta Quota_m$ positive, but somehow far from zero), and (iii) municipalities with $\Delta Quota_m$ around zero. In this way, all municipalities may be treated to some extent.

Motivated by this particular feature, Figure 8 below presents a second and interesting approach useful in future analysis.

Figure 8: New Control and Treatment Definitions



Notes: This figure summarizes the three scenarios: some municipalities $\Delta Quota_m$ negative, but somehow far from zero (we call this a "negative treatment" group – to the left of the purple line), some municipalities $\Delta Quota_m$ positive, but somehow far from zero (we call this a "positive treatment" group – to the right of the purple line), and municipalities with $\Delta Quota_m$ around zero (the new control group – between red lines).

In this sense, we will estimate the specification (6) with some differences. We will separately estimate regressions for positive and negative treatments. That is, we define five different cutoffs $\{c_1, c_2, c_3, c_4, c_5\}$, such that $c_1 \leq c_2 < c_3 < c_4 \leq c_5$. In Figure 8, the purple lines represent c_1 and c_5, the red lines represent c_2 and c_4, and the black line represents c_3. The control group is all the municipalities with $\Delta Quota_m \in [c_2, c_4]$[9]. The positive and negative treatment groups are defined by $\Delta Quota_m \in (c_5, max(\Delta Quota_m)]$ and $\Delta Quota_m \in [min(\Delta Quota_m), c_1)$, respectively. In this approach, we use the treatment as a binary variable[10]. As an expectation, the positive treatment should positively impact GHG emissions since the municipalities with positive $\Delta Quota_m$ may have a growth in the number of beneficiaries (and, consequently, the amount of money) compared to the control group. Inversely, the negative treatment should negatively impact GHG emissions since there are fewer beneficia-

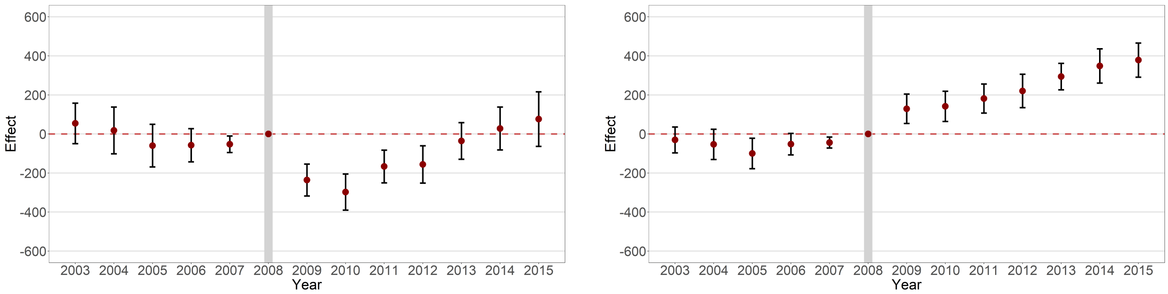
[9]The first example we present, the control group is the same for both regressions, so the municipalities that make up the control group are such that $\Delta Quota_m \in [c_2, c_4]$. In Appendix C, we make a different approach: the control group for the positive treatment differs from the control group for the negative treatment. Hence, there are two different control groups, defined by $\Delta Quota_m \in [c_2, c_3]$ and $\Delta Quota_m \in [c_3, c_4]$.

[10]$Treat_m^+ = \mathbb{1}_{\{\Delta Quota_m \in (c_5, \, max(\Delta Quota_m)]\}}$ for the positive treatment and $Treat_m^- = \mathbb{1}_{\{\Delta Quota_m \in [min(\Delta Quota_m), \, c_1)\}}$ for the negative treatment

ries (and less money from the program) in municipalities with a negative $\Delta Quota_m$ compared to municipalities with a slight variation in this measure.

Let $p(n)$ be the n-th percentile of $\Delta Quota_m$. First, we present the results using $c_1 = p(25)$, $c_2 = p(35)$, $c_4 = p(65)$ and $c_5 = p(75)$. So, the control group is defined by all the municipalities that $\Delta Quota_m \in [p(35), p(65)]$. Figure 9 shows the results for the number of PBF beneficiaries. For the negative treatment (municipalities such that $\Delta Quota_m \in [p(0), p(25))$), there is a negative effect. In contrast, for the positive treatment (municipalities such that $\Delta Quota_m \in (p(75), p(100)]$), there is a positive impact. These results show that the policy changed the composition of beneficiaries differently across municipalities. Municipalities with the highest increase in quota obtained a more significant number of beneficiaries over time than municipalities with a low gain (decrease) proportionally about the total population. We see the opposite for municipalities with adverse changes in quotas. Also note that for negative treatment, the effect dissipates over time. This may be because there was some change in the weighting in 2012 (when there was a new review of the distribution of quotas), compensating the municipalities with a more drastic negative change in 2009.

Figure 9: Heterogeneous Impact on the Number of Beneficiaries

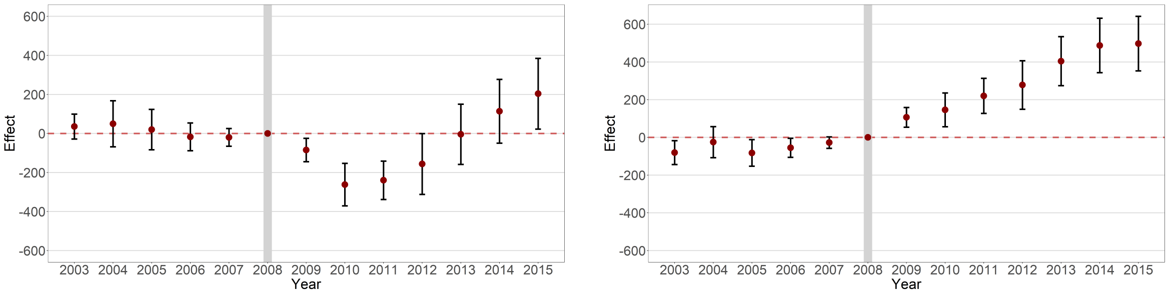


(a) Negative Treatment **(b)** Positive Treatment

Notes: Panel (a) represents the effect of the negative treatment on the number of PBF beneficiaries, with 95% confidence intervals. The control group is defined by the municipalities that $\Delta Quota_m \in [p(35), p(65)]$ and the treatment group is defined by the municipalities that $\Delta Quota_m \in [p(0), p(25))$. Panel (b) represents the effect of the positive treatment on the number of PBF beneficiaries, with 95% confidence intervals. The control group is also defined by the municipalities that have $\Delta Quota_m \in [p(35), p(65)]$ and the treatment group is defined by the municipalities that have $\Delta Quota_m \in (p(75), p(100)]$.

When we analyze, using the same cutoffs, the results for the value of monetary transfers from the *Bolsa Família* program, we see a similar pattern. There is a negative effect for the negative treatment and a positive effect for the positive treatment. Furthermore, for negative treatment, the effect dissipates over time, given that the number of beneficiaries also tends to have no effect from 2013 onwards.

Figure 10: Heterogeneous Impact on the Monetary Value of the Transfers (in thousands)

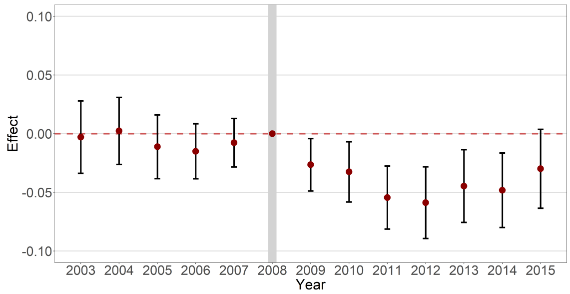


(a) Negative Treatment **(b)** Positive Treatment

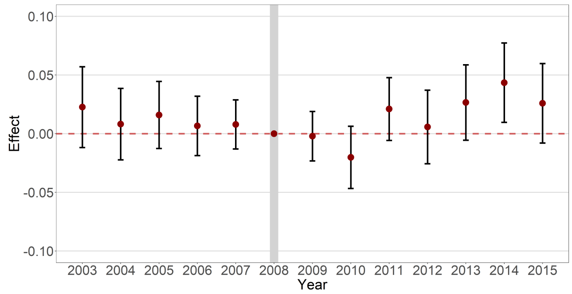
Notes: Panel (a) represents the effect of the negative treatment on the monetary value of the PBF transfers (in thousands), with 95% confidence intervals. All values deflated to 2010. The control group is defined by the municipalities that $\Delta Quota_m \in [p(35), p(65)]$ and the treatment group is defined by the municipalities that $\Delta Quota_m \in [p(0), p(25))$. Panel (b) represents the effect of the positive treatment on the monetary value of the PBF transfers (in thousands), with 95% confidence intervals. All values deflated to 2010. The control group is also defined by the municipalities that have $\Delta Quota_m \in [p(35), p(65)]$ and the treatment group is defined by the municipalities that have $\Delta Quota_m \in (p(75), p(100)]$.

Finally, Figure 11 presents the results for GHG emissions. For the negative treatment, there is a clear and significant negative impact. There is a positive effect for the positive treatment, not always significant, and with a more moderate impact. However, it is possible to state that there is a difference between the two groups. For negative treatment, there is a decrease in the number of beneficiaries, consequently decreasing transfers' monetary value and generating fewer emissions. Notice also that for GHG emission, the effect tends to 0 already in the final analysis period, reflecting the previous dynamics. For positive treatment, there is an increase in the number of beneficiaries and, consequently, in the monetary value, reflecting, even discreetly, an increase in emissions.

Figure 11: Heterogeneous Impact on the GHG Emissions



(a) Negative Treatment



(b) Positive Treatment

Notes: Panel (a) represents the effect of the negative treatment on the GHG emissions (in the log), with 95% confidence intervals. The control group is defined by the municipalities that $\Delta Quota_m \in [p(35), p(65)]$ and the treatment group is defined by the municipalities that $\Delta Quota_m \in [p(0), p(25))$. Panel (b) represents the effect of the positive treatment on the GHG emissions (in the log), with 95% confidence intervals. The control group is also defined by the municipalities that have $\Delta Quota_m \in [p(35), p(65)]$ and the treatment group is defined by the municipalities that have $\Delta Quota_m \in (p(75), p(100)]$.

This difference in impact (an asymmetry) has some possible explanations. The first concerns the literature on income and the environment, which shows that the relationship between these variables is not always predictable. This would explain the difference in the significance and magnitude of the effect. Another possible explanation would be concerning marginal income gain/loss. If a person receives additional money, this does not necessarily become immediate consumption (before, there may be savings or late payments, for example). With less income, however, the impact may be felt first on consumption, as it would be possible to make more immediate cuts.

In Appendix C, we show that the results are similar even using other cutoffs. In this case, $c_1 = c_2 = p(30)$, $c_3 = p(50)$ and $c_4 = c_5 = p(70)$. That is, for the negative treatment: the control group is defined by $\Delta Quota_m \in [p(50), p(70)]$ and the treatment group is defined by $\Delta Quota_m \in [p(0), p(30))$; for the positive treatment: the control group is defined by $\Delta Quota_m \in [p(30), p(50)]$ and the treatment group is defined by $\Delta Quota_m \in (p(70), p(100)]$.

7 (In)Direct Effects

The idea behind local multiplier effects is if the impact on the environment does not come directly from the beneficiaries (our notion of direct impact from the beneficiaries is geographical, that is, the environmental degradation does not necessarily come from the areas where the beneficiaries live). In that sense, the indirect effects represent economic activity, such as people circulation and monetary transfers from beneficiaries' consumption/investment and production change by suppliers induced by the PBF. This indeterminacy between the most degrading regions would signify rearrangement in the economy so that the transfer of money from the program impacts not only the beneficiaries but society as a whole, and the result of more emissions is the result of this new configuration of the economy. In this case, it would be a general equilibrium feature of the program.

We use the 2010 Census Universe database to test it. Census Universe has information about the census tracts, which are geographic divisions made by IBGE with organizational objectives for carrying out the Census. It has information about all Brazilian households. Census tracts are more granular than the municipality level, reaching over 300,000 units. However, the questions in the survey are a subsample from the Sample Census[11]. Here we make an assumption, which we will discuss later: beneficiaries live in more vulnerable areas. That does not seem to be a strong assumption since the PBF beneficiaries are people in situations of greater social vulnerability. The areas, in this case, are the census tracts, and we, therefore, need to create a measure of exposure to vulnerability to understand these areas better.

In short, two hypotheses arise: (i) if the impact is direct, then the cash transfer's effect on the environment is connected to the poorest areas; (ii) if the impact is indirect, then cash transfer has a multiplier effect, such that the environmental impact is due to the broad effects on economic activity.

Hence, we need to classify every census tract as vulnerable or not. To do so, we follow two different strategies. In both, we try to classify the areas but with different approaches. Afterward, we merge the resulting prediction, a territorial grid classification, with a georeferenced environment base (Appendix D presents a simple example of this merge. In this case, the fines data are used). This is why the evidence of an indirect effect is suggestive: there is no georeferenced GHG emission data with the necessary granularity up to our knowledge. However, it is essential to remember that fines are also affected by the treatment and have a pattern of effect similar to that of GHG emissions. Below we summarize each strategy.

- **Strategy 1:**

  (i) *Instituto de Pesquisa Econômica Aplicada (IPEA)* classifies municipalities as vulnerable or not according to the Sample Census variables. This classification has three pillars: human capital, infrastructure, and income/employment;

[11] Variables related to the residence's infrastructure, such as access to treated water and sewage, related to household income, and associated with the demographic composition of the household. In Strategy 1 below, we specify which variables were chosen.

(ii) Train a model to predict this *dummy* using Household Census variables. The variables need to be in the Universe Census too. Aggregate variables in the Sample Census (municipality level) and the Census Universe (census tract level): people per household, income, access to treated water, bathroom at home, garbage collection, electricity, literacy, race, underage, and gender.

(iii) Predict census tracts' vulnerability using Census Universe variables;

(iv) Prediction as a proxy for vulnerability. In this case, we use the Logit prediction. Table 2 below presents the proportion of equal responses between different models. The models predict equivalently. In addition, the models perform pretty well ($90\% - 95\%$). So, every model will provide almost the same final result. As in Strategy 2, we will be practically compelled to use a Logit, we also use the Logit model in Strategy 1 to maintain the standard.

Table 2: Models Predictions

	k-nn	Bagging	Random Forest	Boosting	Logit	SVM
k-nn	1	0.9655	0.9706	0.9672	0.9598	0.9775
Bagging	0.9655	1	0.9842	0.9803	0.9632	0.9730
Random Forest	0.9706	0.9842	1	0.9807	0.9752	0.9828
Boosting	0.9672	0.9803	0.9807	1	0.9671	0.9751
Logit	0.9598	0.9632	0.9752	0.9671	1	0.9723
SVM	0.9775	0.9730	0.9828	0.9751	0.9723	1

Notes: Each value represents the proportion of equal predictions between two models. Each model performs very well (accuracy rate between 90% and 95%).

- **Strategy 2:**

(i) Sample Census (at the individual level) has information on whether the individual is a PBF beneficiary. Train a model to predict PBF using income and municipality *dummies*.

(ii) Use the average income in the census tract and municipality *dummies* to predict PBF. Notice that the training model is at the individual level. The classification, however, is at the census tract level. In this case, being classified is like a measure of exposure to the PBF: if the census tract receives 1, then probably too many families are low-income in this census tract.

(iii) Use the Logit prediction as a proxy for vulnerability.

Finally, merge the vulnerability classification of the territorial mesh of census tracts (Strategy 1 or Strategy 2[12]) with the fines data (we have information on the fine's latitude and longitude). We are interested in estimating the following regression, separating into two cases: for municipalities with $\Delta Quota_m < 0$ and municipalities with $\Delta Quota_m > 0$.

$$y_{imt} = \phi_i + \theta_t + \alpha_{m,t} + + \sum_{\lambda \neq 2008} \beta_\lambda \times \mathbb{1}_{\{t=\lambda\}} \times \hat{z}_i + \varepsilon_{imt} \tag{7}$$

where y_{imt} is equal to 1 if census tract i of municipality m in year t has fine and $\hat{z}_i = \mathbb{1}_{\{\hat{p}_i > 0.5\}}$ is the prediction[13] of one of the strategies. ϕ_i, θ_t, and $\alpha_{m,t}$ are census tract, year, and municipality-year fixed effects, respectively. The error term is bootstrapped and clustered at the municipality level.

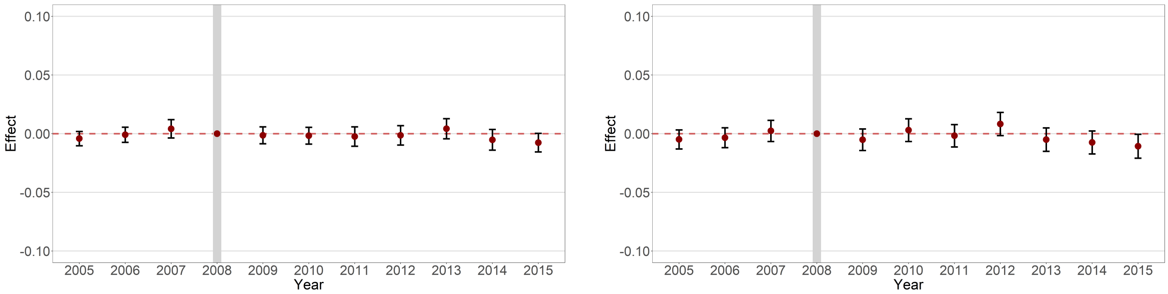
The logic in estimate separating into two regressions is as follows: suppose that $\Delta Quota_m > 0$ for all municipalities, and the effect is direct. As shown in the scenario where $\Delta Quota_m > 0$ in Section 6, there are more PBF beneficiaries and, consequently, more cash transfer money. This leads to more GHG emissions. As the beneficiaries are most likely to live in the most vulnerable region, there would be a difference in environmental degradation between vulnerable and not vulnerable areas. In such a case, we would expect β_λ to be positive after the methodology change in 2009. Therefore, $\beta_\lambda = 0, \forall \lambda$, brings evidence that the effect is indirect. It is possible to think in a similar story, just reversing the signs, supposing $\Delta Quota_m < 0$ and direct effect. In this case, $\beta_\lambda = 0, \forall \lambda$, would also bring evidence of the indirect effect.

First, we present the results for Strategy 1. Figure 12 indicates suggestive evidence about the local multiplier effects. There is no difference between vulnerable areas and non-vulnerable areas. This is consistent for municipalities that $\Delta Quota_m < 0$ and for municipalities that $\Delta Quota_m > 0$.

[12] A third and simpler strategy would be to define vulnerability based on income thresholds in each census sector. This strategy generates results similar to the previous strategies. This strategy, like the others, can also present problems: a poor census sector, but with some people with high income, can create a higher average income to the point of not classifying this sector as vulnerable. In this section, we discuss another approach that possibly avoids this potential problem.

[13] The optimal cutoff is approximately 0.5. The results are similar, even altering this value.

Figure 12: Indirect Effect Results (Strategy 1)

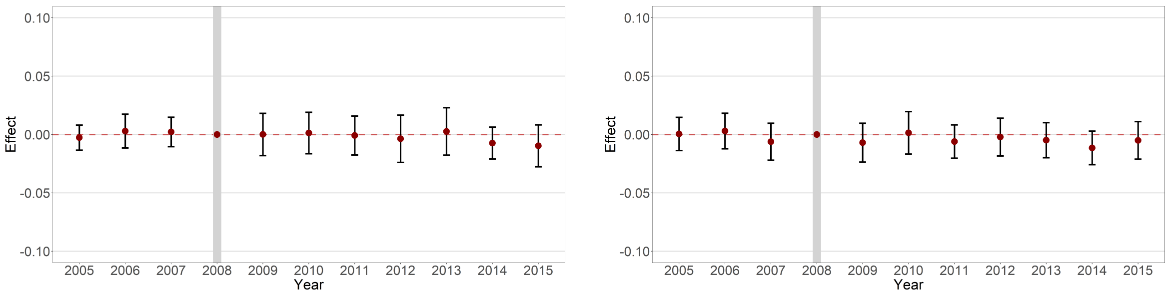


(a) $\Delta Quota_m < 0$ **(b)** $\Delta Quota_m > 0$

Notes: This figure presents evidence about the local multiplier effects using Strategy 1 to classify vulnerable areas. Panel (a) represents the impact of vulnerability on fines using only municipalities that $\Delta Quota_m < 0$. Panel (b) represents the impact of vulnerability on fines using only municipalities that $\Delta Quota_m > 0$. The standard errors were computed using 1,000 repetitions for both.

Finally, Figure 13 presents the results for Strategy 2, reinforcing the previous results and bringing more evidence about the general equilibrium effect of *Bolsa Família*. As in strategy 1, the values are all statistically not different from zero. Both results bring favorable evidence that the effect on GHG emissions is not an exclusive factor of program beneficiaries.

Figure 13: Indirect Effect Results (Strategy 2)



(a) $\Delta Quota_m < 0$ **(b)** $\Delta Quota_m > 0$

Notes: This figure presents evidence about the local multiplier effects using Strategy 2 to classify vulnerable areas. Panel (a) represents the impact of vulnerability on fines using only municipalities that $\Delta Quota_m < 0$. Panel (b) represents the impact of vulnerability on fines using only municipalities that $\Delta Quota_m > 0$. The standard errors were computed using 1,000 repetitions for both.

8 Robustness Checks

This section provides a series of modifications to the main specification. First, we redefine the denominator of the treatment variable. Second, we exclude the extremes from $\Delta Quota_m$ and population size. Third, we change how we make inferences using microregion clusters or allowing for spatial correlation. Finally, we show the results using the latest developments in DiD.

8.1 Other treatment definitions

The first three items below use the number of households in 2006, 2009, and 2010, respectively, as a form of standardization for the variation in the number of quotas. As the number of households is calculated according to the Censuses (2000 and only in 2010), the values for 2006 and 2009 are corrected for population growth. As for 2010, the value used comes from the 2010 Census. The last item constructs the counterfactual quota without the transitory poverty correction. In short, more municipalities are left with a positive delta.

(i) Weighted by the number of households in 2006 (correcting by population growth):

$$\Delta Quota_m := \frac{Quota_m^{2009} - CountQuota_m^{2009}}{Dom_{ms}^{2000} n_m^{[2000,2006]}}$$

(ii) Weighted by the number of households in 2000 (correcting by population growth):

$$\Delta Quota_m := \frac{Quota_m^{2009} - CountQuota_m^{2009}}{Dom_{ms}^{2000} n_m^{[2000,2009]}}$$

(iii) Weighted by the number of households in 2010:

$$\Delta Quota_m = \frac{Quota_m^{2009} - CountQuota_m^{2009}}{Dom_m^{2010}}$$

(iv) Defining the counterfactual without 1.18 factor:

$$CountQuota_m^{2009} = \frac{Poor_{ms}^{2000} \cdot n_{ms}^{[2000,2006]}}{\sum_{k \in s} \left(Poor_{ks}^{2000} n_{ks}^{[2000,2006]} \right)} \cdot Poor_s^{2006}$$

In this, we maintain the original treatment variable configuration:

$$\Delta Quota_m := \frac{Quota_m^{2009} - CountQuota_m^{2009}}{Pop_{ms}^{2000} n_m^{[2000,2006]}}$$

Finally, we define the treatment dummy as $Treat_m = \mathbb{1}_{\{\Delta Quota_m > 0\}}$.

See the results in Appendix E for all these new treatment definitions. First, for the first three treatments: the distributions maintain a similar shape, changing mainly the weights of the tails. The medians remain approximately equal to 0. The results remain identical to the original when we use the binary measure for the treatment. For continuous treatment, the result is similar, but it is important to pay attention to the scale. As the $\Delta Quota_m$ measure changes, the effect has different magnitudes. However, the effect pattern remains the same. As for the last treatment alternative, the binary treatment result (it receives 1 if the $\Delta Quota_m > 0$) is very similar to the original result. For the continuous measure, the result is a little different, losing significance in some periods (but still with a positive effect in others), suggesting that with this measure, there is a reordering between municipalities.

8.2 Excluding the extremes

Here we exclude the 1st and 99th percentiles from $\Delta Quota_m$ and population size, in a possible assumption that municipalities that gained (or lost) quota more sharply or municipalities whose population size is large enough to change the emission pattern. The results do not change. See Figures E.5 and E.6.

8.3 Inference

We propose two different approaches for inference: (i) cluster the standard error at the microregion level (set of similar municipalities in the same region) and (ii) account for spatial correlation in the standard error (Conley, 1999) so that neighboring municipalities are correlated. The interpretation remains the same (Figures E.7 and E.8).

8.4 New approaches in DiD

Considering the new advances in Difference-in-Differences, we estimate the principal regression using the Doubly Robust estimator (Sant'Anna and Zhao, 2020). This allows exploring the differences between two-way fixed effects and DiD when controls are present. We use the package proposed in Callaway and Sant'Anna (2021) (recalling that, in our case, the treatment period is the same for all municipalities – so it is only one group). Despite some differences, the results have an interpretation similar to the one we have been using (see Appendix E).

9 Conclusions

This article seeks to understand the relationship between cash transfers and the environment. The relationship between these two components is uncertain, and the existing literature shows that the relationship depends on the economic characteristics of the studied location. In our case, we use a change in methodology that occurred in 2009 in the *Bolsa Família* program. As a main contribution, we present the medium-term spillover effects of the program on GHG emissions based on a Difference-in-Differences design. We found a positive effect on emissions.

However, this effect does not appear to result from a specific channel. We found no effect on deforestation, areas of agriculture, and livestock production. Such results primarily indicate the production side. With this, the result may be the result of more economic activity, provided by the increase in income from the transfer, increasing the range of consumption and investment, and allowing greater movement of people and money. This general equilibrium characteristic may be fundamental to explaining the increase in GHG emissions.

Our results indicate that the GHG emissions expansion is a consequence of economic activity driven by the increase in money originating from the *Bolsa Família*. This is the local multiplier effect or simply the indirect effect. If so, looking for urbanization changes seems to be an essential step. Perhaps new forms of consumption (in the primary empirical strategy, most variables used were focused on the production side), well-established in the literature, and urban mobility explain a part of the increase in GHG emissions. Still, finding mechanisms on the production side can also be a response via the consumption side, also representing evidence of an effect on economic activity.

In this line, it is possible to refine the indirect effect analysis. We have used models to predict poor (or vulnerable) areas. Not necessarily do these areas represent the PBF beneficiaries' place of residence. Although the different strategies return results with the same interpretation, it is possible to improve this analysis: in *CadÚnico*, there is the PBF beneficiary address. This information would allow us to geolocate the PBF beneficiary and know precisely what census tract the PBF recipient lives in. This approach would generate an even more credible notion of the most vulnerable census tracts (in this case, those with a high proportion of beneficiaries). We can revisit the previous analysis with this new attempt. Furthermore, it is possible to use a broader range of data with georeferencing. Databases that capture urban mobility seem appropriate to better investigate the potential mechanisms mentioned above.

Finally, if the hypothesis of a general equilibrium effect of the PBF is correct, the increase in emissions can be seen as a spillover effect of economic activity. Thus, negative environmental impacts are also associated with significant economic impacts. Cash transfers should be considered concomitantly with other tools to align poverty eradication and climate agendas.

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For Online Publication

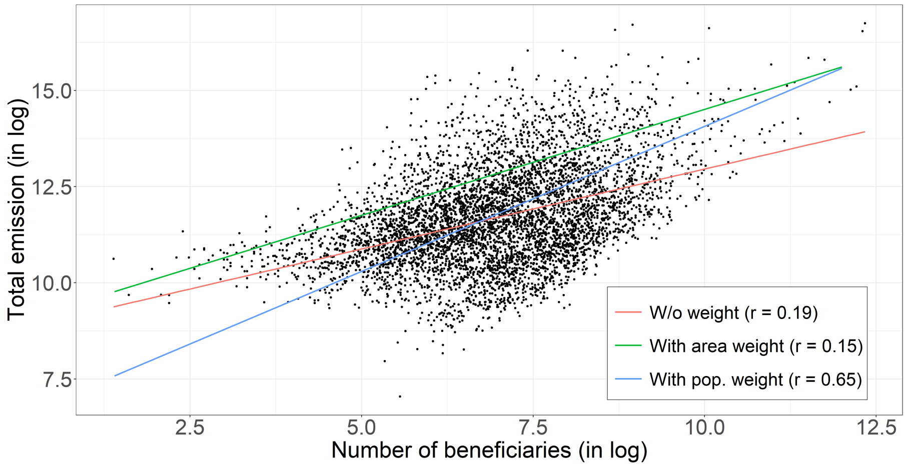
Online Appendix to "Cash Transfers and The Environment"

Paulo Mencacci Daniel Da Mata Vladimir Ponczek

July 26, 2023

A Descriptive

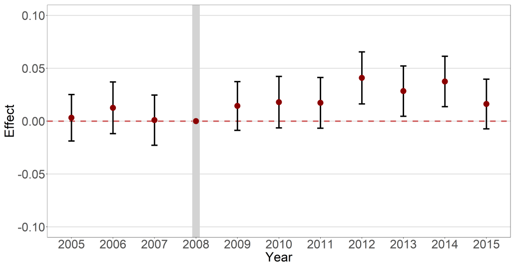
Figure A.1: Correlation between GHG Emissions and The Number of Beneficiaries



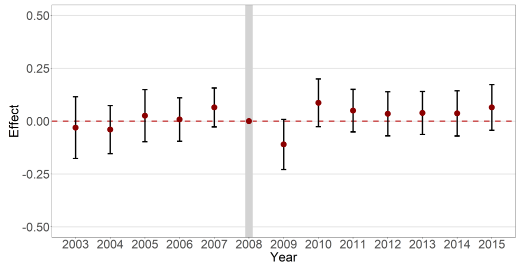
Notes: Correlations between GHG Emissions (in the log) and the number of beneficiaries (in the log), in 2012. The points represent the municipalities. The green and blue lines use area and population weights, while the red line does not have weights.

B Possible Mechanisms

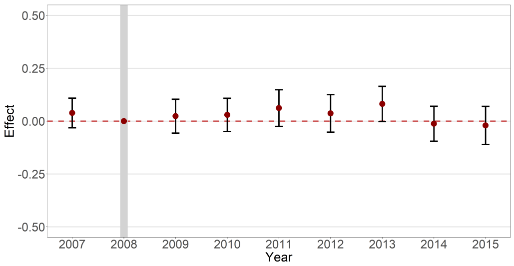
Figure B.1: Possible Mechanisms with the Binary Measure



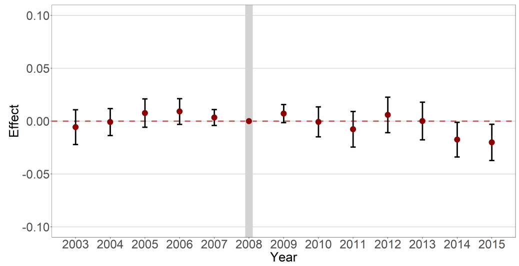
(a) Fines (source: Ibama)



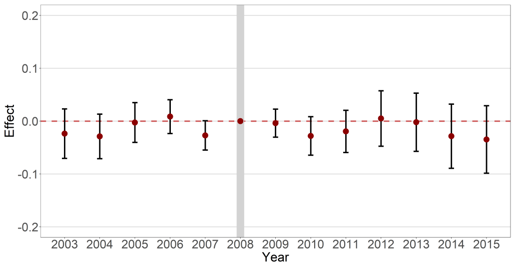
(b) Deforestation (source: PRODES)



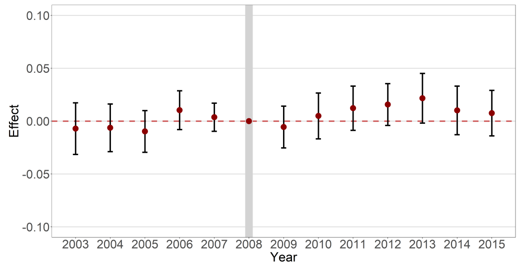
(c) Deforestation Alerts (source: DETER)



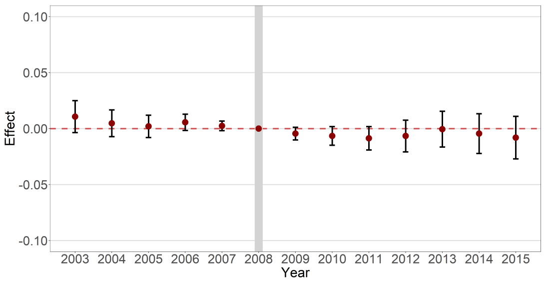
(d) Forest Area (source: MapBiomas)



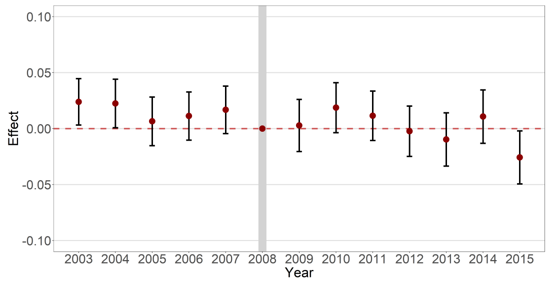
(e) Farming Area (source: PAM)



(f) Heads of Cattle (source: PPM)



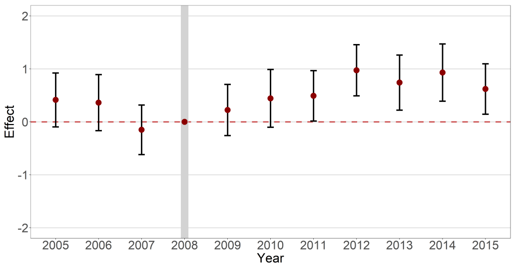
(g) Agriculture Area (source: MapBiomas)



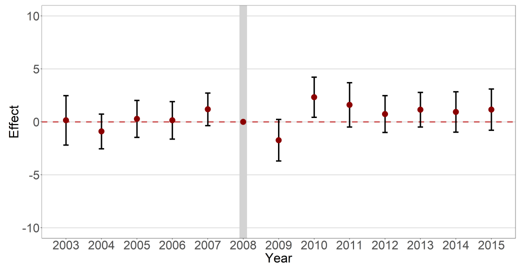
(h) Fire (source: BdQueimadas)

Notes: Panel (a): the probability of fines imposed by Ibama as the dependent variable. Municipality m in year t receives one if a fine is imposed on the municipality in this specific year; it receives 0 if no fine is imposed in that year. Panel (b): deforestation area in the log transformation using the PRODES source. This database does not account for the whole country (only for the municipalities in the Leval Amazon). Panel (c): the probability of alert via DETER. Municipality m in year t receives one if an alert is generated about the municipality in this specific year; it receives 0 if there is no alert in that year. Panel (d): forest area, in the log transformation, from MapBiomas. Differently from the PRODES data, this data provides the area of the municipality covered by forest, while PRODES provides the deforested area in the year. Also, this data covers the entire country. That is, it provides information for all municipalities. Panel (e): farming area, in the log transformation provided by the PAM, a survey similar to the Census. This source also provides information for all municipalities. Panel (f): number of heads of cattle in the log transformation, provided by PPM, a survey similar to the Census. This source also provides information for all municipalities. Panel (g): agriculture area, in the log transformation, from MapBiomas. All municipalities are covered. Panel (h): the probability of fires, provided by BdQueimadas. Municipality m in year t receives one if it has a fire in this specific year; it receives zero if there is no fire that year. For this regression, we also controlled for rain and temperature. All regressions with 95% confidence intervals. The treatment variable is the binary measure. These regressions indicate no additional attempts to change the soil (either by burning or deforestation). The fact that there was no increase in the productive area also means this factor. Still, there does not seem to be an intensification of production, given the stability in beef production. The only change seems to occur with the probability of a fine occurring, which increases over time, with a pattern similar to GHG emissions. The rest of the regressions don't seem to have any effect. The regressions involving forest areas may even indicate some effect. However, this effect is negative for deforestation (PRODES), contrary to the impact on emissions. For forest area (MapBiomas), this effect is negative; that is, there is a decrease in forest cover, but the delay is considerable, not representing the change found in the main specification.

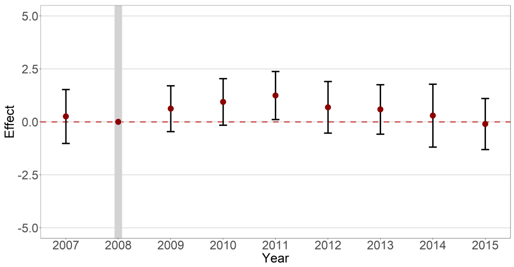
Figure B.2: Possible Mechanisms with the Continuous Measure



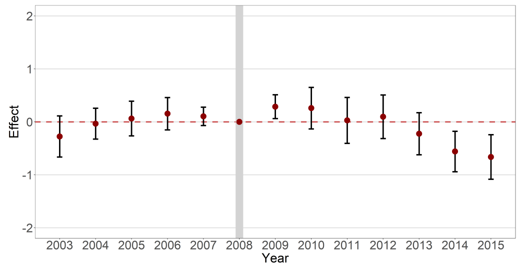
(a) Fines (source: Ibama)



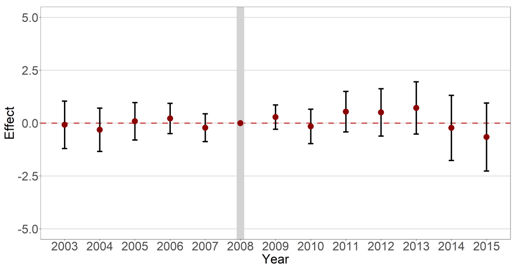
(b) Deforestation (source: Prodes)



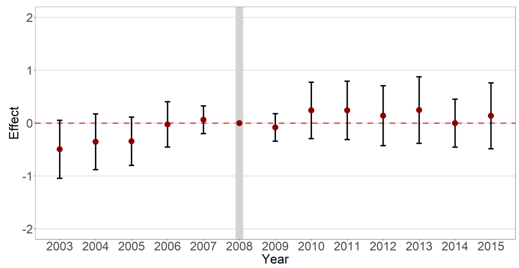
(c) Deforestation Alerts (source: DETER)



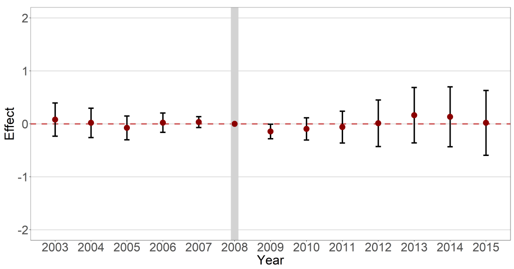
(d) Forest Area (source: MapBiomas)



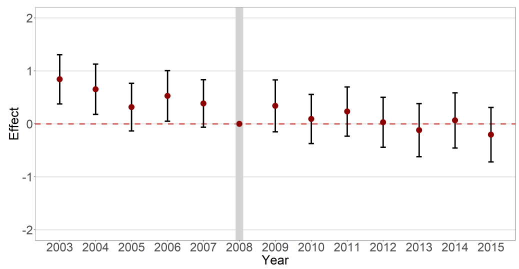
(e) Farming Area (source: PAM)



(f) Heads of Cattle (source: PPM)



(g) Agriculture Area (source: MapBiomas)

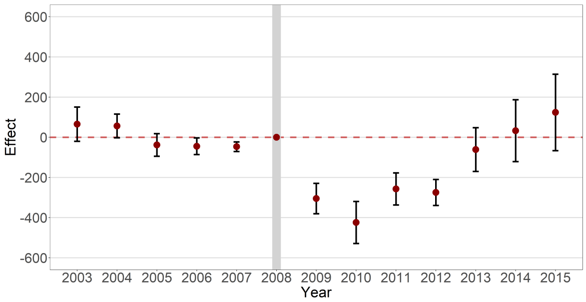


(h) Fire (source: BdQueimadas)

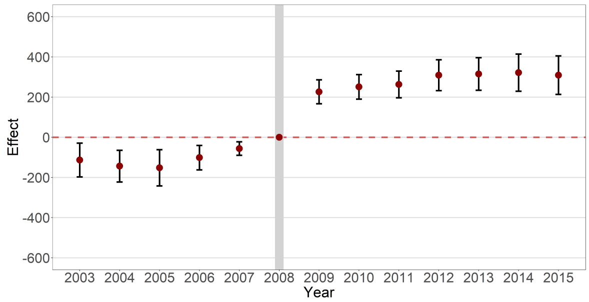
Notes: Same description as the Figure B.1. The only difference: the treatment variable is the continuous measure ($\Delta Quota_m$).

C Heterogeneity Analysis

Figure C.1: Heterogeneous Impact on the Number of Beneficiaries



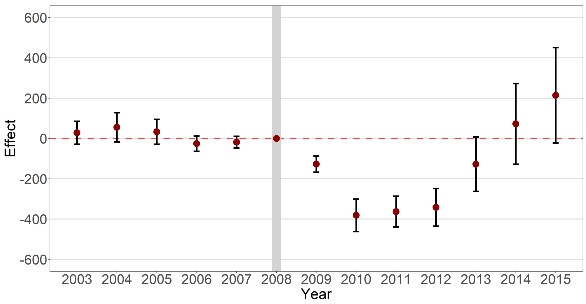
(a) Negative Treatment



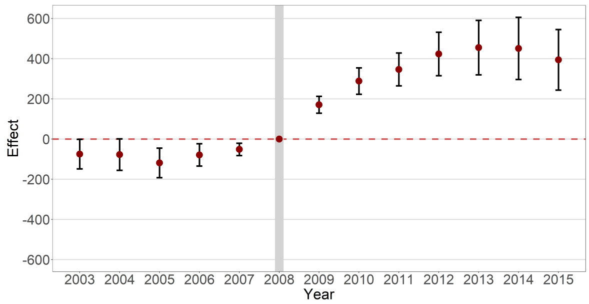
(b) Positive Treatment

Notes: Panel (a) represents the effect of the negative treatment on the number of PBF beneficiaries, with 95% confidence intervals. The control group is defined by the municipalities that $\Delta Quota_m \in [p(50), p(70)]$ and the treatment group is defined by the municipalities that $\Delta Quota_m \in [p(0), p(30))$. Panel (b) represents the effect of the positive treatment on the number of PBF beneficiaries, with 95% confidence intervals. The control group is also defined by the municipalities that have $\Delta Quota_m \in [p(30), p(50)]$ and the treatment group is defined by the municipalities that have $\Delta Quota_m \in (p(70), p(100)]$.

Figure C.2: Heterogeneous Impact on the Monetary Value of the Transfers (in thousands)



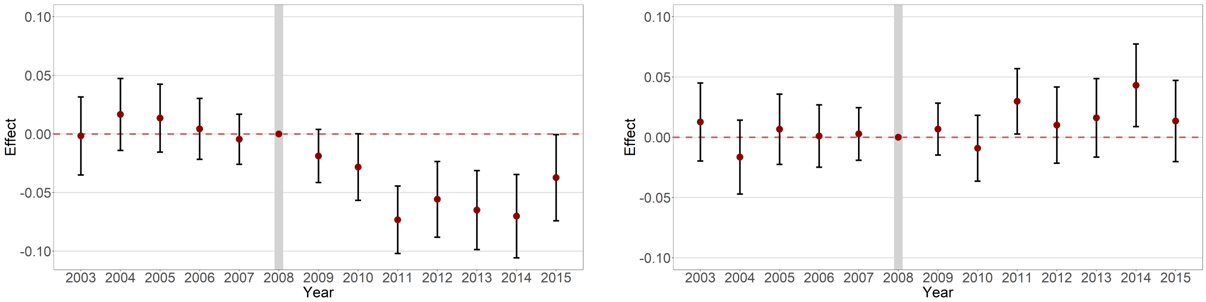
(a) Negative Treatment



(b) Positive Treatment

Notes: Panel (a) represents the effect of the negative treatment on the monetary value of the PBF transfers (in thousands), with 95% confidence intervals. All values deflated to 2010. The control group is defined by the municipalities that $\Delta Quota_m \in [p(50), p(70)]$ and the treatment group is defined by the municipalities that $\Delta Quota_m \in [p(0), p(30))$. Panel (b) represents the effect of the positive treatment on the monetary value of the PBF transfers (in thousands), with 95% confidence intervals. All values deflated to 2010. The control group is also defined by the municipalities that have $\Delta Quota_m \in [p(30), p(50)]$ and the treatment group is defined by the municipalities that have $\Delta Quota_m \in (p(70), p(100)]$.

Figure C.3: Heterogeneous Impact on the GHG Emissions



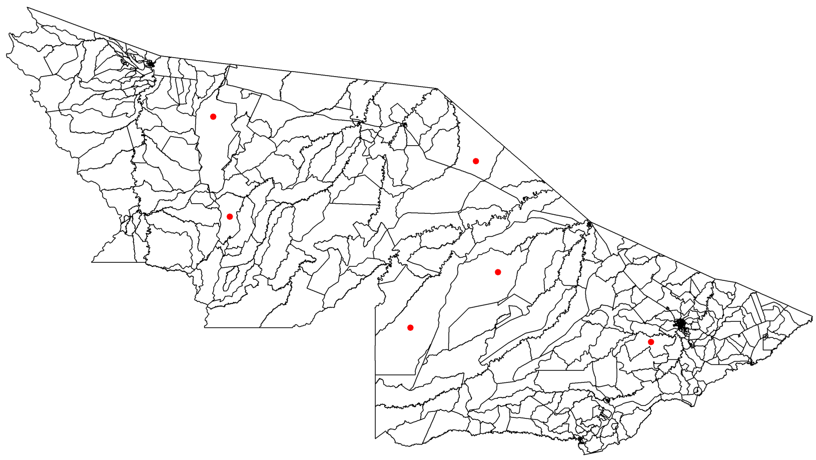
(a) Negative Treatment

(b) Positive Treatment

Notes: Panel (a) represents the effect of the negative treatment on the GHG emissions (in the log), with 95% confidence intervals. The control group is defined by the municipalities that $\Delta Quota_m \in [p(50), p(70)]$ and the treatment group is defined by the municipalities that $\Delta Quota_m \in [p(0), p(30))$. Panel (b) represents the effect of the positive treatment on the GHG emissions (in the log), with 95% confidence intervals. The control group is also defined by the municipalities that have $\Delta Quota_m \in [p(30), p(50)]$ and the treatment group is defined by the municipalities that have $\Delta Quota_m \in (p(70), p(100)]$.

D Map

Figure D.1: Territorial Grid of Census Tracts and Coordinates of Fines

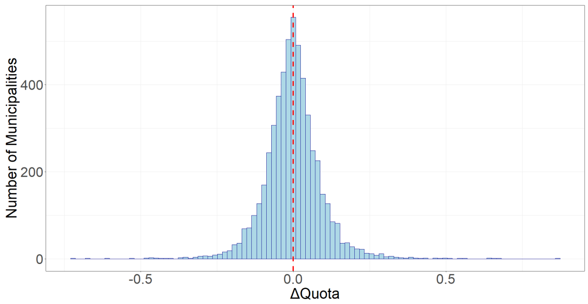


Notes: Simple hypothetical example of the merge. Red points represent the fine. The territorial division represents the census tracts. A census tract with a red point inside receives 1, while the census tract without any point receives 0. This territorial division represents the state of Acre.

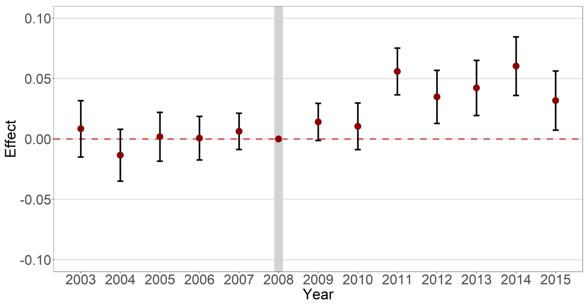
E Robustness Checks

E.1 Results for the other treatment definitions

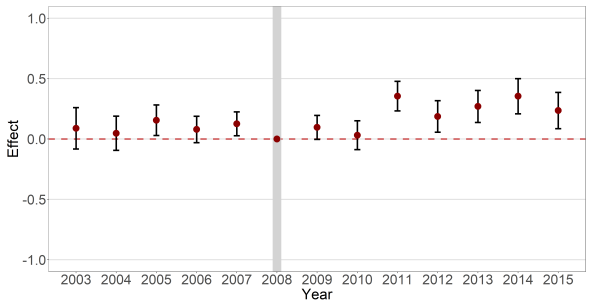
Figure E.1: Alternative Treatment: Using the Number of Households in 2006



(a) $\Delta Quota_m$ distribution



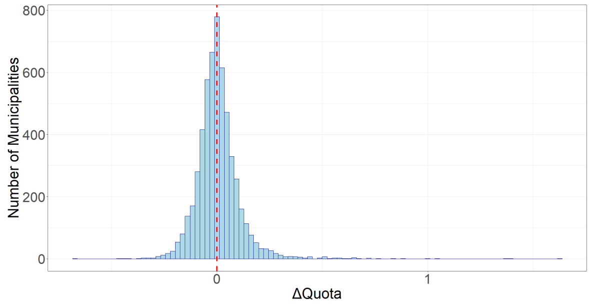
(b) Binary Treatment



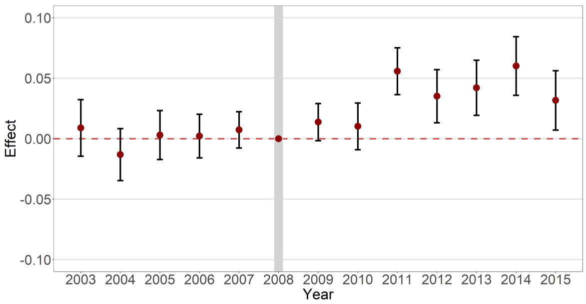
(c) Continuous Treatment

Notes: When $\Delta Quota_m := \frac{Quota_m^{2009} - CountQuota_m^{2009}}{Dom_{ms}^{2000} n_m^{[2000,2006]}}$. Panel (a) shows the $\Delta Quota_m$ distribution, Panel (b) shows the result for GHG emissions in the log transformation, with 95% confidence intervals, using the main specification and binary treatment, and Panel (c) shows the result for GHG emissions in the log transformation, with 95% confidence intervals, using the main specification and continuous treatment.

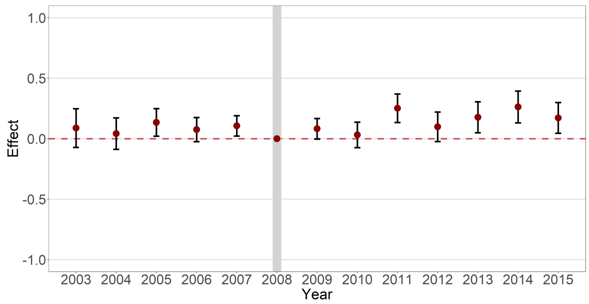
Figure E.2: Alternative Treatment: Using the Number of Households in 2009



(a) $\Delta Quota_m$ distribution



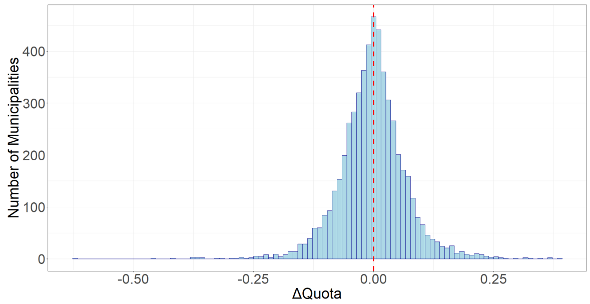
(b) Binary Treatment



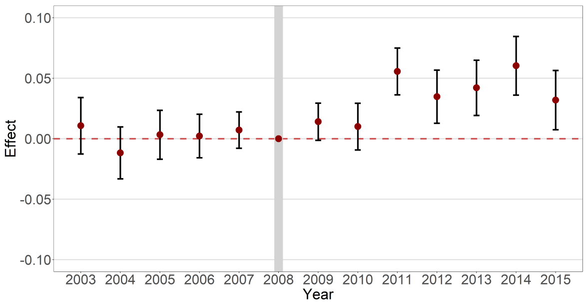
(c) Continuous Treatment

Notes: When $\Delta Quota_m := \frac{Quota_m^{2009} - CountQuota_m^{2009}}{Dom_{ms}^{2000} n_m^{[2000,2009]}}$. Panel (a) shows the $\Delta Quota_m$ distribution, Panel (b) shows the result for GHG emissions in the log transformation, with 95% confidence intervals, using the main specification and binary treatment, and Panel (c) shows the result for GHG emissions in the log transformation, with 95% confidence intervals, using the main specification and continuous treatment.

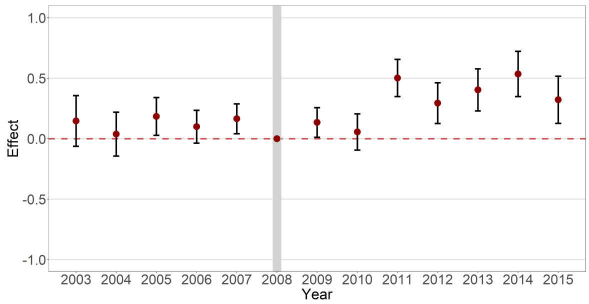
Figure E.3: Alternative Treatment: Using the Number of Households in 2010



(a) $\Delta Quota_m$ distribution



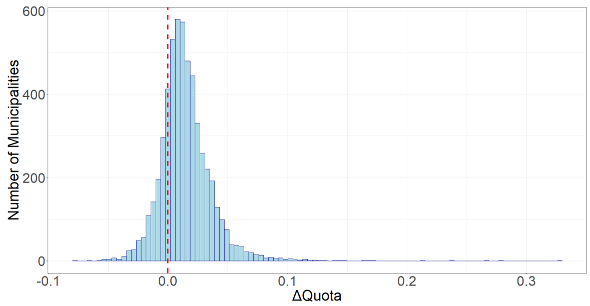
(b) Binary Treatment



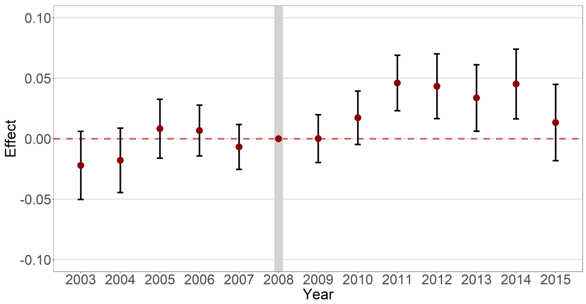
(c) Continuous Treatment

Notes: When $\Delta Quota_m := \frac{Quota_m^{2009} - CountQuota_m^{2009}}{Dom_{ms}^{2010}}$. Panel (a) shows the $\Delta Quota_m$ distribution, Panel (b) shows the result for GHG emissions in the log transformation, with 95% confidence intervals, using the main specification and binary treatment, and Panel (c) shows the result for GHG emissions in the log transformation, with 95% confidence intervals, using the main specification and continuous treatment.

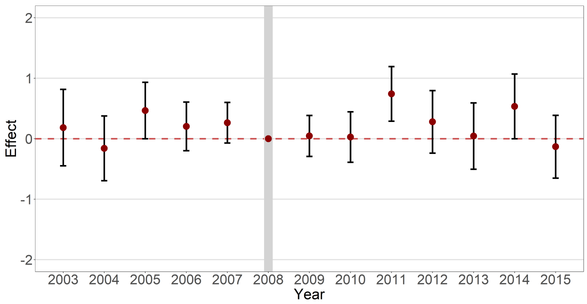
Figure E.4: Alternative Treatment: Without 1.18 Factor



(a) $\Delta Quota_m$ distribution



(b) Binary Treatment

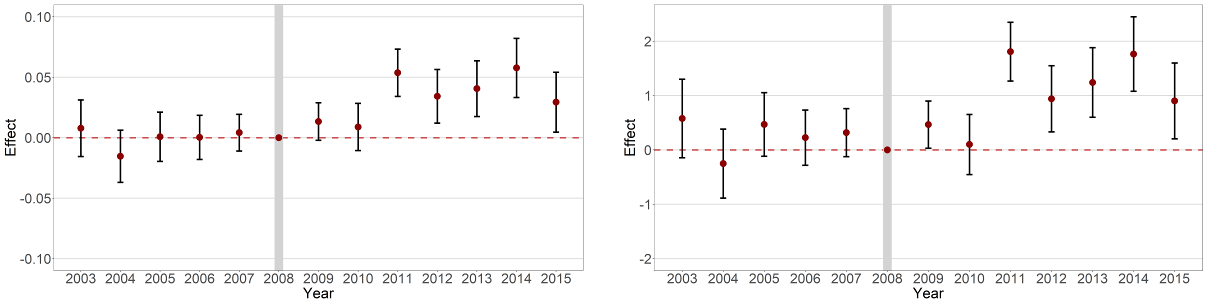


(c) Continuous Treatment

Notes: When $CountQuota_m^{2009} = \frac{Poor_{ms}^{2000} \cdot n_{ms}^{[2000,2006]}}{\sum_{k \in s}\left(Poor_{ks}^{2000} n_{ks}^{[2000,2006]}\right)} \times Poor_s^{2006}$ and $\Delta Quota_m := \frac{Quota_m^{2009} - CountQuota_m^{2009}}{Pop_{ms}^{2000} n_m^{[2000,2006]}}$. Panel (a) shows the $\Delta Quota_m$ distribution, Panel (b) shows the result for GHG emissions in the log transformation, with 95% confidence intervals, using the main specification and binary treatment, and Panel (c) shows the result for GHG emissions in the log transformation, with 95% confidence intervals, using the main specification and continuous treatment.

E.2 Results excluding the extremes

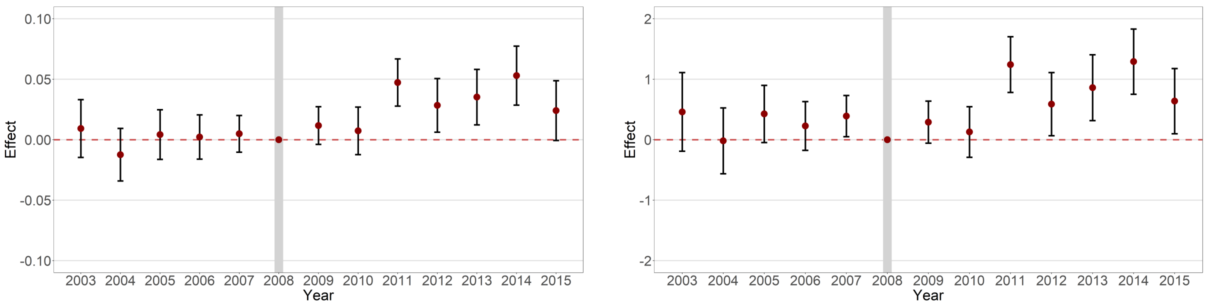
Figure E.5: GHG Emissions Results Excluding the $\Delta Quota_m$ Extremes



(a) GHG emissions (binary treatment) **(b)** GHG emissions (continuous treatment)

Notes: This figure shows the results when excluding first and last percentiles from $\Delta Quota_m$, with 95% confidence intervals. Panel (a) represents the effect on GHG emissions (in the log) using the binary treatment variable. Panel (b) also represents the effect on GHG emissions (in the log) but uses the continuous treatment variable.

Figure E.6: GHG Emissions Results Excluding the Population Size Extremes

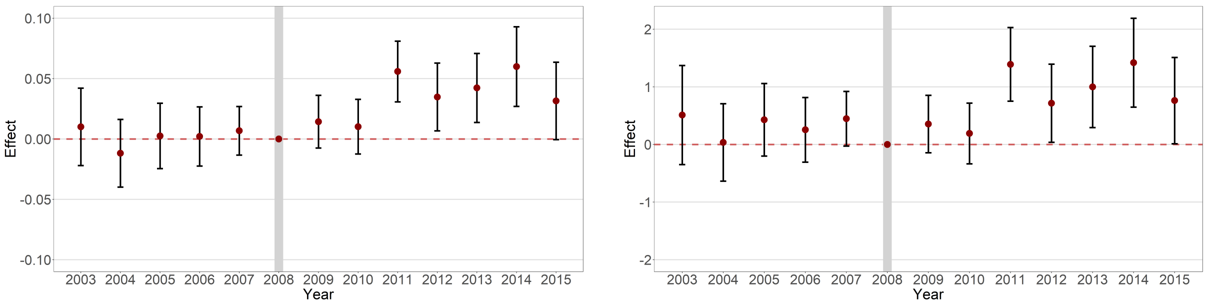


(a) GHG emissions (binary treatment) **(b)** GHG emissions (continuous treatment)

Notes: This figure shows the results when excluding first and last percentiles from municipalities' population size (in 2000), with 95% confidence intervals. Panel (a) represents the effect on GHG emissions (in the log) using the binary treatment variable. Panel (b) also represents the effect on GHG emissions (in the log) but uses the continuous treatment variable.

E.3 Inference

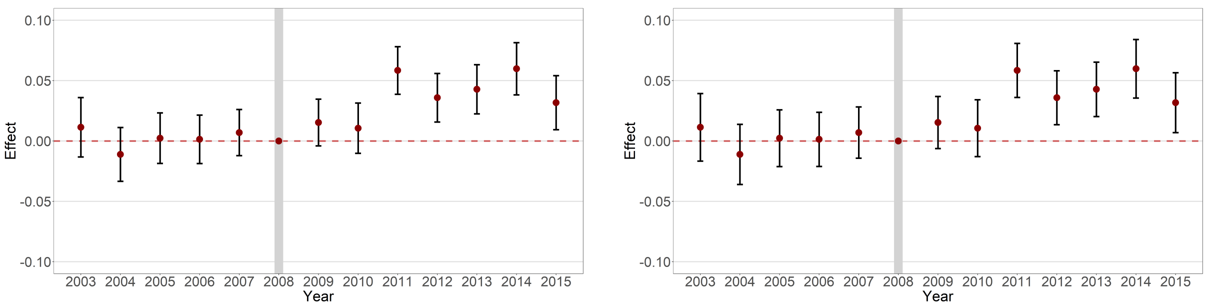
Figure E.7: GHG Emissions Results Clustering at the Microregion Level



(a) GHG emissions (binary treatment) **(b)** GHG emissions (continuous treatment)

Notes: This figure shows the results when the standard are clustered at the microregion level, with 95% confidence intervals. Panel (a) represents the effect on GHG emissions (in the log) using the binary treatment variable. Panel (b) also represents the effect on GHG emissions (in the log) but uses the continuous treatment variable.

Figure E.8: GHG Emissions Results Allowing for Spatial Correlation

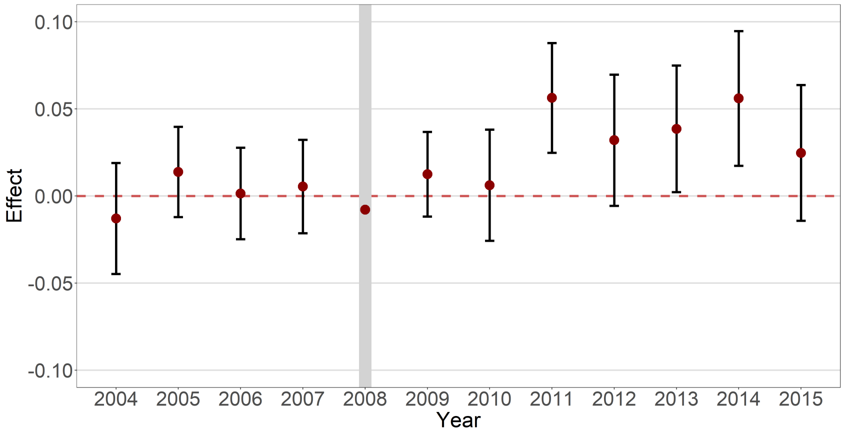


(a) 25km radius **(b)** 50km radius

Notes: This figure shows the results using the Conley regressions approach, with 95% confidence intervals. Panel (a) represents the effect on GHG emissions (in the log) using a 25km radius (around the city center). Panel (b) also represents the effect on GHG emissions (in the log) but using a 50km radius.

E.4 New Approaches in DiD

Figure E.9: Results for GHG Emissions using the Doubly Robust Estimator



Notes: The effect of the PBF methodology change on the GHG Emissions using the Doubly Robust Estimator. There is only one group in this case since the treatment time is unique. Uniform confidence intervals (1,000 repetitions) with $\alpha = 0.05$. Clustered at the municipality level.