# Impact of natural disasters on local public finance: Evidence from droughts and floods in Brazil

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**Abstract**

Natural disasters can cause substantial damage to human lives, the environment, and the economy, leading to financial strain on subnational governments. This study examines the impact of extreme weather events on the local public finances in Brazil, focusing on government funding strategies for relief measures and policies to reduce future risks associated with such hazards. We leverage Standard Precipitation and Evapotranspiration Index (SPEI) data to identify extreme floods and droughts in 5,474 municipalities from 1997 to 2019. Then, we estimate the effects of these disasters on local public finance by employing an approach that combines a difference-in-differences estimator with a matching method and allows treatments with switching on and off behavior. Our findings reveal that droughts do not significantly impact intergovernmental transfers, leading to financial strain for the affected municipalities. Conversely, floods increase the grants received by local governments, improving their fiscal balances. However, this better fiscal situation does not affect the spending in flood mitigation areas (urbanism and the environment), suggesting a moral hazard problem related to the overreliance on resources from higher-level governments.

***Keywords:*** *natural disaster; flood; drought; SPEI; local finance; decentralization; Brazil; difference-in-differences; matching.*

***JEL Classification:*** *H71, H72, H74, O13, O54, Q54*

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# 1 Introduction

Natural disasters, such as floods, droughts, and hurricanes, may have devastating effects on human lives, the environment, and the economy. They impose local fiscal stress by incurring rehabilitation costs while simultaneously lowering tax revenues (Jerch, Kahn, & Lin, 2023). Therefore, higher-level governments typically provide assistance through disaster-related and non-disaster-related transfers (Deryugina, 2017). Nevertheless, it is unclear if local public finance will improve or deteriorate and whether budget allocations will prioritize hazard-prevention measures. The central authority's decision on the amount of financial aid may be influenced by political interests (Garrett & Sobel, 2002) and media attention (Eisensee & Stromberg, 2007). Additionally, local governments might exhibit moral hazard behavior by relying on future expected grants, rather than investing in preventive measures (Goodspeed & Haughwout, 2012; Wildasin, 2008). Furthermore, extreme weather events have distinct characteristics. Droughts develop gradually over time due to prolonged dryness, while floods can occur suddenly, causing immediate and noticeable damage. The speed and magnitude of the response to an event may vary, which poses an empirical question regarding the impact of natural disasters on local public finance and whether there are heterogeneous responses based on the hazard type.

This study examines the impact of extreme weather events on local public finance in Brazil. We aim to understand how governments fund unexpected expenses and whether affected areas reduce spending on policies to mitigate future hazard-related losses. We leverage data from 1997 to 2019, covering 5,474 municipalities[1], and we break down the analysis by floods and droughts. Brazil is an interesting case when it comes to natural disaster relief. The federal and state governments may provide financial assistance, but there is no set formula for how it should be done, making it a political decision. As a developing country with limited financial resources and state capacity, it is unclear whether higher-level governments will have the means to provide assistance. Therefore, previous findings from developed countries may not be directly applicable to this specific context.

The local public financial data from 2000[2] to 2019 was obtained from the Public Sector Accounting and Tax Information System (Siconfi), which is managed by the National Treasury Secretariat (STN). To minimize potential bias related to political interests in reporting natural disasters in Brazil, we utilized the 1981-2022 Standard Precipitation and Evapotranspiration Index (SPEI) dataset, provided by Gebrechorkos et al. (2023) to identify municipalities affected by extreme cases of floods and droughts from 1997 to 2019. This approach is similar to the strategy employed by Albert, Bustos, and Ponticelli (2022) in their analysis of the impacts of Brazilian droughts on labor and capital allocation.

[1] Actually, Brazil has 5,570 municipalities, but some of them were established between 2001 and 2013. In order to maintain consistent data over time, we aggregated the new local jurisdictions with their "parent" municipalities into microregions by using Ehrl (2017) dataset.

[2] There is financial information from 1991 to 1999, but with a significant amount of missing data from the municipalities in the North and Northeast regions, which concentrate the poorer municipalities in Brazil. As a result, we gathered financial data from 2000 onwards.

We estimate the effects of floods and droughts on local public finance by employing Imai, Kim, and Wang's (2023) method, which combines a difference-in-differences estimator with a matching method on panel data, and allows treatments with switching on and off behavior. It involves matching each treated observation (a unit may be treated more than once) with control observations from other units within the same time period that share an identical treatment history. This approach better captures the nature of extreme weather events as floods and droughts tend to frequently occur in the same areas.

Our study has two main findings. First, the amount of higher-level government aid varies between municipalities experiencing droughts and those facing floods. Those affected by droughts do not receive significant transfers from higher-level governments. This does not affect the fiscal balance in the first year of extreme drought. However, if the drought persists into the next year, the financial strain becomes more evident as services tax revenue lowers significantly, and there is a shift of current expenditures to capital investments. In contrast, municipalities affected by floods see a significant improvement in their financial balance due to substantial increases in grants, not only during the flood years but also in the aftermath, with the increase in capital transfers.

Second, there is evidence of disaster-related moral hazard associated with intergovernmental financial aid. Even though flood-affected municipalities receive increased grants, their spending on urban development and environmental areas, which are typically related to flood mitigation measures, does not significantly increase. Instead, these resources tend to be allocated towards other capital investments and agricultural activities. Conversely, jurisdictions that experienced extreme droughts, which did not receive increased transfers from higher-level governments during the emergency, maintained higher spending on environmental and agricultural measures in the aftermath. This spending may involve purchasing cisterns and water trucks to deal with the drought, for example.

We contribute to two main strands in the economic literature. The first one is the local financial response to natural shocks, which is a relatively new field that expands the analysis on economic indicators, such as employment, population, and wages (Belasen & Polachek, 2008; Strobl, 2011), to the public sector. Most of its empirical research focuses on hurricanes and floods, which are the hazards that cause the most damage in the United States. It indicates a negative effect on local tax revenue, leading to disaster-related expenditures being primarily financed by an increase in transfers (Deryugina, 2017; Jerch et al., 2023; Miao, Abrigo, Hou, & Liao, 2022). We expand on prior research by examining how floods and droughts affect local public finances in Brazil. Our analysis reveals that droughts have a non-significant impact on transfers and a negative impact on tax revenue, while floods have a positive effect on grants and no significant impact on tax revenue. Additionally, we explore different types of intergovernmental transfers and their mechanisms to provide further understanding of our findings.

We also contribute to the literature on decentralization and natural disasters, which explores the complex interplay among different levels of government in managing and mitigating the impacts of such events. Theoretical models, such as those by Wildasin (2008) and Goodspeed and Haughwout (2012), highlight the potential underinvestment in hazard-preventive infrastructure due to a soft budget constraint (Kornai, 1979; Kornai, Maskin, & Roland, 2003), a situation where a local government is likely to receive financial assistance from the central authority. Empirical studies in this literature yield mixed results on whether decentralization is effective in mitigating the impact of natural disasters. Skidmore and Toya (2013) and Escaleras and Register (2012) suggested that decentralized countries tend to experience lower disaster-related fatalities, while Miao, Shi, and Davlasheridze (2021) found that US states with more decentralized natural resource expenditures suffered greater economic losses from floods and storms. We find that municipalities affected by floods do not significantly increase environmental and urbanism expenditures despite receiving substantial intergovernmental transfers, suggesting an underinvestment in hazard-mitigation measures.

The remainder of this paper is organized as follows: Section 2 provides an overview of civil defense in Brazil. Section 3 provides the data used in this study, such as SPEI and local finance variables, and presents descriptive statistics. Section 4 outlines the empirical strategy employed in this study. Section 5 discusses the results of the impacts of droughts and floods on local government finances. Section 6 concludes with a summary of findings, limitations, and policy implications.

## 2 Civil Defense in Brazil

Brazil experiences two primary natural disasters: floods and droughts. Flooding is a frequent and widespread natural hazard that causes significant socioeconomic and environmental damage globally (Barredo, 2009). In particular, urban areas are often highly susceptible to hydrological hazards due to the high density of impermeable surfaces, such as concrete and asphalt, which increases runoff during heavy rainfall and overwhelms drainage systems. On the other hand, droughts are periods of significantly low moisture that typically cover extensive areas, leading to negative impacts on natural systems and economic sectors (Ault, 2020), which accumulate over time.

Climate change is leading to more frequent and severe natural disasters, requiring increased efforts from governments and society. In this context, civil defense plays a vital role in coordinating across various levels of government and non-governmental organizations to implement preventive measures, ensure emergency preparedness, provide rapid disaster response, and support post-disaster recovery. Specifically, the Brazilian civil defense has undergone significant transformations in recent decades, shifting from providing assistance to disaster-affected populations to implementing public policies for hazard prevention and monitoring (Kuhn et al., 2022).

The National System for Civil Defense was established in 1988 and shared responsibilities with all levels of government. In the event of a natural disaster, the mayor of an affected municipality needs to report the hazard's occurrence by declaring an emergency or a state of calamity. The governor may support the local decree by issuing another declaration, which typically occurs when many municipalities in the state are affected by a hazard simultaneously. The federal government, through the Secretariat of Civil Defense (SEDEC) of the Brazilian Ministry of Regional Development, evaluates the decree and decides whether to recognize the disaster. If it does, the central authority issues an order acknowledging the emergency or state of calamity and provides financial and operational assistance to the subnational entity.

There is no public record before 2012 regarding the criteria used to identify an emergency or a state of public calamity, except for the definition of public calamity as "the abnormal situation caused by adverse factors that deprive the population of meeting their basic needs and affect community activities, the preservation of human lives, and the security of material goods" and an emergency as the situation that "may become a public calamity" (Federal Decree No. 97,274/1988). Only in 2012, a normative instruction defined rules to recognize an abnormal situation as a disaster, such as impacting the local government's ability to handle the crisis and resulting in a minimum amount of human, material, environmental, and/or economic losses (Table 7).

The criteria for triggering federal aid have been established, but some are still subjective, such as the ability to handle the crisis. This makes the process still prone to political interests in reallocating financial resources to local governments. Evidence of this includes politically important subnational governments receiving more aid (Cavalcanti, 2018; Larreguy & Monteiro, 2014) in election years (Garrett & Sobel, 2002). Additionally, in the 2007 guide for reporting natural disasters, the federal government explicitly informs municipalities that the decree "should not be made with the sole objective of resorting to the financial resources". Therefore, there is a potential selection bias in natural disaster reporting and recognizing process, which makes SEDEC's hazard records potentially unsuitable for use in causal inference methods.

# 3 Data

## 3.1 Standard Precipitation and Evapotranspiration Index (SPEI)

To overcome the potential bias in using the reported disaster dataset, we identify droughts and floods by using the Standard Precipitation and Evapotranspiration Index (SPEI), which is one of the most used indicators to monitor droughts[3]. It is obtained by transforming water balance (= precipitation − potential evapotranspiration) into standard deviations (Vicente-Serrano, Beguería, & López-Moreno, 2010). SPEI values can be categorized into seven levels of dryness/wetness, which provide a standardized framework for

[3]The Standard Precipitation Index (SPI) is the recommended indicator by the World Meteorological Organization for identifying and monitoring droughts (Hayes, Svoboda, Wall, & Widhalm, 2011). It is similar to SPEI, but does not account for temperature changes, which affects the water cycle of regions.

assessing and monitoring moisture conditions (Table 1). These levels range from "extremely wet" conditions, represented by values greater than or equal to 1.83, to "extremely dry" conditions, represented by values less than or equal to $-1.65$. The system also includes intermediate categories such as "severely wet," "moderately wet," "near normal," "moderately dry," and "severely dry," each corresponding to specific ranges of SPEI values.

Table 1: SPEI categories

| **SPEI** | **Categories** |
|---|---|
| $\geq$ 1.83 | extremely wet |
| 1.43 to 1.82 | severly wet |
| 1.0 to 1.42 | moderately wet |
| -0.83 to 0.99 | near normal |
| -0.84 to -1.27 | moderately dry |
| -1.28 to -1.64 | severely dry |
| $\leq$ -1.65 | extremely dry |

Sources: Agnew (2000) and Danandeh Mehr et al. (2020)

This is a flexible index that can be applied in distinct regions with varying sizes and climates, while still allowing for comparison among them. SPEI can also handle different timescales for identifying types of droughts and their impacts (Table 2). The SPEI of 1-month timescale, SPEI-1, can identify meteorological droughts that affect water availability. Using SPEI-3[4] and SPEI-6, it is possible to recognize areas with agriculture stress due to soil moisture deficits (agricultural droughts). Greater timescales, from 12 to 24 months, reveal longer trends in water streams and storages, allowing the identification of hydrological droughts.

Table 2: SPEI timescales, drought types and impacts

| **Timescale (months)** | **Drought type** | **Impacts** |
|---|---|---|
| 1 | meteorological | precipitation/water deficits |
| 3–6 | agricultural | crop yield reduction/failure, and soil moisture deficits |
| 12–24 | hydrological | water shortage in streams or storages such as reservoirs, lakes, lagoons, and groundwater |

Sources: Svoboda, Hayes, and Wood (2012) and IPCC (2023).

In this study, we obtained a high-resolution SPEI dataset from Gebrechorkos et al. (2023) and aggregated the grid cells at the municipality level[5] from 1997 to 2019. Using municipalities' SPEIs and the SEDEC's reported natural disaster dataset, Table 3 classifies declared droughts (floods) based on the lowest (highest) monthly SPEI value of the reported year. Although most of the reported disasters were severe and extreme cases, one-third of the decrees occurred during near normal or moderate wetness/dryness levels, evidencing a potential selection bias due to political interest.

[4]While SPEI-1 is the standardized monthly water balance, SPEIs with longer timescales, SPEI-$N$, are calculated by averaging $N$ consecutive monthly values before transforming into standard deviations.

[5]Municipalities' administrative borders and their urban areas were obtained from the Brazilian Institute of Geography and Statistics (IBGE).

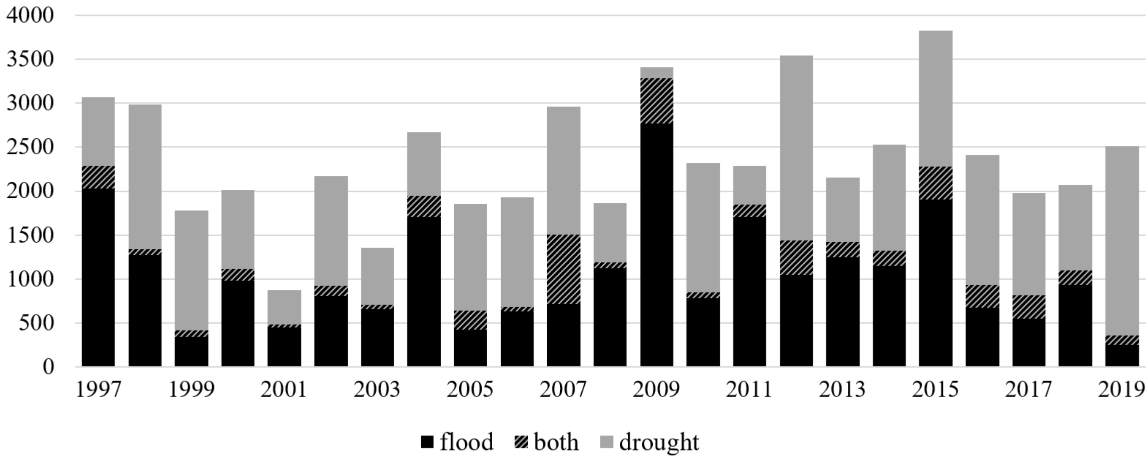
Table 3: SPEI category and reported hazards (1997–2019)

| **SPEI category** | **Droughts reported** | **Floods reported** |
|---|---|---|
| Extremely wet | – | 40.4% |
| Severely wet | – | 27.9% |
| Moderately wet | – | 17.7% |
| Near normal | 12.6% | 14.0% |
| Moderately dry | 23.9% | – |
| Severely dry | 29.8% | – |
| Extremely dry | 33.7% | – |
| Total | 23,856 | 13,854 |

Notes: Reported droughts categorized using SPEI-3, and reported floods categorized using SPEI-1 (urban).
Sources: SEDEC and Gebrechorkos et al. (2023).

Empirically, a large fraction of total losses are caused by a small number of major events (Wildasin, 2008), so we focused on extreme cases of hazards. We considered that a local government was hit by a flood in a year if there was at least one month with SPEI-1 $\geq 1.83$ in its urban areas. For drought recognition, we considered the 3-month timescale SPEI lower than $-1.65$ to identify periods of agricultural stress that affect the local economy, mainly in rural areas. Using these selected thresholds, Figure 1 presents the 54,598 natural disaster occurrences in municipalities divided by year. There is a significant annual variability in the number of municipalities affected by these disasters. Some years, such as 2009 and 2011, show a higher prevalence of floods, while others indicate a higher incidence of droughts, like 2012 and 2019. At most, 3,826 administrative units were affected by a hazard in a single year, which represents 70.8% of the total municipalities (5,474).

Figure 1: Municipalities affected by natural disasters by year, using SPEI thresholds




Source: Gebrechorkos et al. (2023)

## 3.2 Local finance

The 1988 Federal Constitution enabled political autonomy and fiscal decentralization (Rodden, 2003), granting the responsibility for providing basic education, primary health care, social assistance, sanitation, water supply, land use management, and public transportation. To fund these public services, a larger proportion of resources started being shared with the municipalities by increasing the amount of existing grants and creating new ones. This process of resource distribution has led to vertical fiscal imbalance, where a subnational entity relies excessively on intergovernmental transfers to fund its operations. As a result, only 6% of the total revenue comes from local tax collection (Table 4), whose main sources are services activities (ISSQN tax) and real estate properties (IPTU tax).

On the other hand, grants account for 86% of municipal revenue, and since there are several of them, we focus on the four major ones, which represent 88% of the total grant revenue (Table 4). First, the Municipal Participation Fund (FPM) allocates 24.5% of income tax (IR) and industrialized products tax (IPI) to states, which is then redistributed to local governments according to population ranges. Its purpose is to provide greater per capita resources to smaller jurisdictions. However, the method of distributing a fixed transfer amount for each population range leads to inconsistencies in transfer redistribution (Boueri, Monasterio, Mation, & Silva, 2013; Tomio, 2002). For example, as the population within a range increases, the per capita amount received declines since the transfer for that range remains constant. Furthermore, if a population shift leads a municipality to move to a different range, the FPM per capita may either rise or fall, depending on whether the change in population is small or large (Figure 4). As a result, it is difficult to analyze a disaster's influence on this transfer.

The second most important grant by volume is the VAT share, which accounts for 25% of the total amount collected of value-added tax (ICMS) on goods and services at the state level. This is a return-type transfer, as the main distribution criterion is the municipality's value-added (at least 75%), with the remaining (at most 25%) determined by state law[6].

Unlike the previous two, the Educational Funds (FUNDEF and FUNDEB) and the Unified Health System (SUS) are conditional grants, as they must be allocated specifically to education and public health services, respectively. Established in 1998, the Fund for the Development of Fundamental Education (FUNDEF) covered expenses exclusively for public elementary and middle schools (*ensino fundamental*). Each state has its own FUNDEF, which is financed by 15% of state and municipal primary taxes and transfers (FPE, ICMS, IPI-exp, and FPM). All collected resources are distributed among all municipalities within the same state based on the number of students. In 2007, this fund was replaced by the Fund for Development and Maintenance of Basic Education and Teacher Valorization (FUNDEB), which included additional levels of basic education (early childhood, high school, and adult/continuing), added more tax sources (ITCMD, IPVA, and ITR), and increased contributions from 15% to 20%. Furthermore, if a state's educational transfer per capita falls below a nationally defined threshold, the federal government supplements the transfer with its own resources. In this study, we consider FUNDEF's transfer amounts to

[6] For example, the state of Sao Paulo's VAT share criteria is based on value-added (76%), population (13%), local tax revenue (5%), cultivated area (3%), water reservoirs area (0.5%), protected areas (0.5%), and the remaining (2%) is equally distributed among municipalities.

be equivalent to FUNDEB's from 2000 to 2006.

The SUS transfer aims to provide universal coverage for health services and has distinct sharing rules. It can be divided into two types: agreement transfers, which are paid on a case-by-case basis, and "fund-to-fund" transfers, which involve automatic transfers to state and municipal health funds. These transfers support health programs, including basic to high-complexity care, health surveillance, and pharmaceutical care, and the distribution is often based on per capita indicators or health program production levels and is allocated to essential health services across the country (Mendes, Miranda, & Cosio, 2008; Rocha, 2019).

Established in 1969 to mitigate the impact of natural disasters, the Fund for Public Calamity (FUNCAP) has remained inactive due to the absence of a financial source, which has not been defined through federal regulation. In the absence of a specific grant for hazards, we assume capital transfers as a proxy for disaster-related aid. They typically result from agreements between local administrations and higher-level governments and are related to public investments.

This situation of high reliance on resources from higher levels of government may encourage municipalities' imprudent fiscal behavior, as they anticipate a bailout from the central authority (Aldasoro & Seiferling, 2014; Kornai, 1979; Kornai et al., 2003). In Brazil, borrowing restrictions tightened in the 1990s with the introduction of fiscal rules[7] to tackle subnational debt and hyperinflation. Consequently, municipalities have limited capacity to boost revenue through credit operations[8], in addition to their own tax collection. In the context of natural disasters, local governments may limit their spending on expensive disaster preparedness and avoidance policies, assuming that higher levels of government will likely provide them with financial and operational aid in future hazards (Goodspeed & Haughwout, 2012; Wildasin, 2008). In this study, we assume expenses in urbanism, environment and agriculture as proxies for disaster relief and mitigation measures.

The 2000-2019 financial information was obtained from the Public Sector Accounting and Tax Information System (Siconfi), managed by the National Treasury Secretariat (STN). All monetary values are in 2019 Brazilian reais (R$).

### 3.3 Descriptive statistics

Considering that extreme natural events frequently reoccur in some regions and have happened numerous times before the period examined in this study, we have set multiple baselines from 2000 to 2019 for comparative analysis. This approach reduces the statistics sensitivity to the selection of a single baseline year and allows for a dynamic comparison

[7] After the public state banks were privatized, state governments ceased issuing treasury bills. Consequently, subnational entities had to obtain approval from the federal government for borrowing, which was contingent upon meeting fiscal targets such as financial surplus, capping personnel expenses, and limiting indebtedness.

[8] Although the recognition of a state of public calamity or emergency temporarily suspends the fulfillment of fiscal targets, subnational entities are required to return to meeting these targets within a year.

between the municipalities affected by a hazard in a given year with those that were not, using the previous year as a reference point (when conditions were normal for both).

Table 4 reveals municipalities that experienced droughts and floods in the following year already exhibited higher total surpluses, revenues, and expenditures compared to those that did not. Tax revenues are comparable across all four groups, while the transfers are slightly higher in jurisdictions hit by hazards. Borrowing is higher in municipalities hit by flood, and is comparable between non-drought and drought groups. Similarly, the expenditures in local governments are slightly higher in the disaster groups, but the environmental spending in municipalities affected by flood.

The literacy rate, age, working-age population rate, rural household rate, and Gini index show minimal variation across the different groups. In disaster-affected jurisdictions, GDP per capita is slightly lower, and the economy relies more on agriculture and less on industry. Income is considerably higher, and the population is lower in municipalities affected by floods and droughts. These indicators were obtained from the Brazilian Institute of Geography and Statistics (IBGE).

The comparative analysis indicates that municipalities affected by disasters already have distinct characteristics, likely due to the recurring natural disasters in these areas. Therefore, the applied empirical strategy uses a matching technique to obtain a more credible control group and take into account the history of previous disaster occurrences.

## 4 Empirical strategy

We employ Imai et al. (2023) approach to estimate the impact of natural disasters on public finance, which combines a matching method with a difference-in-difference estimator.

In recent studies on the difference-in-differences (DiD) method, researchers have found that using the standard two-way fixed effects (TWFE) regressions with panel data could lead to biased estimates when dealing with heterogeneous treatment effects (Goodman-Bacon, 2021; Imai & Kim, 2021; Roth, Sant'Anna, Bilinski, & Poe, 2023). This is especially true for complex treatment designs involving non-binary treatments and with switching on and off behavior (De Chaisemartin & D'Haultfœuille, 2023). Some of the newly proposed DiD estimators that address this bias assume staggered treatment (Borusyak, Jaravel, & Spiess, 2024; Callaway & Sant'Anna, 2021; Sun & Abraham, 2021), meaning that once a unit becomes treated, it remains treated until the end of the analysis period. However, they may not be suitable for capturing the effects of natural disasters as these events exhibit switching on and off behavior that may not correspond with the assumptions of the estimators.

To our knowledge, only Imai et al. (2023) and de Chaisemartin and d'Haultfoeuille (2024) proposed DiD estimators that address non-staggered treatment adoption. However, their methodologies differ in defining reference points for estimating contemporaneous and lead effects.

Table 4: Municipality baseline statistics by natural disaster (2000–2019)

| Variable | non-drought | drought | non-flood | flood |
|---|---|---|---|---|
| **Total Surplus**$^{\times}$ | 286.2 | 331.8 | 276.1 | 327.9 |
| **Total Revenue**$^{\times}$ | 2,902.9 | 3,183.6 | 2,911.8 | 3,093.6 |
| Tax Revenues$^{\times}$ | 187.1 | 187.7 | 187.7 | 176.9 |
| Services Tax$^{\times}$ | 78.1 | 76.2 | 77.3 | 73.6 |
| Property Tax$^{\times}$ | 40.0 | 36.8 | 41.4 | 32.4 |
| Transfers$^{\times}$ | 2,503.6 | 2,770.5 | 2,510.2 | 2,705.4 |
| Municipal Participation Fund$^{\times}$ | 1,027.7 | 1,174.9 | 1,032.7 | 1,149.2 |
| VAT Share$^{\times}$ | 549.2 | 612.3 | 541.9 | 600.6 |
| Basic Education Fund$^{\times}$ | 440.9 | 477.0 | 450.3 | 468.0 |
| Health System Transfers$^{\times}$ | 185.1 | 205.8 | 193.2 | 196.9 |
| Capital Transfers$^{\times}$ | 113.6 | 124.2 | 111.3 | 134.5 |
| Borrowing$^{\times}$ | 13.1 | 13.2 | 12.5 | 13.9 |
| **Total Expenditure**$^{\times}$ | 2,620.2 | 2,852.9 | 2,639.6 | 2,765.4 |
| Current Expenditure$^{\times}$ | 2,296.6 | 2,520.2 | 2,326.1 | 2,405.1 |
| Capital Expenditure$^{\times}$ | 323.9 | 333.2 | 314.0 | 360.5 |
| *by function* | | | | |
| Urbanism$^{\times}$ | 246.8 | 251.6 | 245.4 | 269.8 |
| Agriculture$^{\times}$ | 68.6 | 72.1 | 61.3 | 75.1 |
| Environment$^{\times}$ | 16.1 | 16.5 | 16.8 | 14.6 |
| **Municipality characteristics** | | | | |
| GDP$^{\times}$ | 19,560 | 18,998 | 19,698 | 19,020 |
| Agriculture (%) | 22.0 | 22.7 | 21.4 | 23.0 |
| Industry (%) | 14.2 | 13.7 | 14.3 | 13.4 |
| Services (%) | 31.0 | 31.6 | 31.8 | 30.5 |
| Government (%) | 32.9 | 31.9 | 32.5 | 33.2 |
| Population | 39,662 | 27,685 | 38,878 | 28,445 |
| Income | 886.7 | 943.7 | 891.7 | 915.1 |
| Literacy (%) | 83.5 | 84.8 | 84.1 | 83.9 |
| Age | 30.3 | 31.1 | 30.3 | 30.9 |
| Working age population (%) | 64.0 | 64.7 | 64.2 | 64.3 |
| Rural household (%) | 37.6 | 35.3 | 36.2 | 37.2 |
| Gini Index | 0.53 | 0.52 | 0.53 | 0.52 |
| Mayor in President's coalition | 11.1 | 11.3 | 12.1 | 9.5 |
| Observations | 61,995 | 18,018 | 62,137 | 17,383 |

Notes: $^{\times}$R$ per capita. We established different baselines, using years before natural shocks as reference points. The drought and flood groups include municipalities in years that are not experiencing a disaster and are affected by one in the next period. Non-drought and non-flood categories consist of units in years that are not and remain not impacted by a hazard in the following period. Sources: STN, IBGE, and TSE.

Considering a binary treatment design, the de Chaisemartin and d'Haultfoeuille's (2024) approach initially defines groups of potential switchers-in and potential switchers-out who are, respectively, non-treated and treated in the first period of the panel data. The average treatment effect on the treated (ATT) calculation in the first group is similar to the estimator proposed by Callaway and Sant'Anna (2021) without covariates, as it defines each unit's first treatment status change (becoming treated) as its reference point to compute the event study effects and uses only untreated units of potential switchers-in group as controls. The effect of becoming untreated can also be calculated with the potential switchers-out group, using the treated units as controls.

This approach has two limitations when dealing with recurring natural hazards over a long period. First, the de Chaisemartin and d'Haultfoeuille (2024)'s estimator (and other

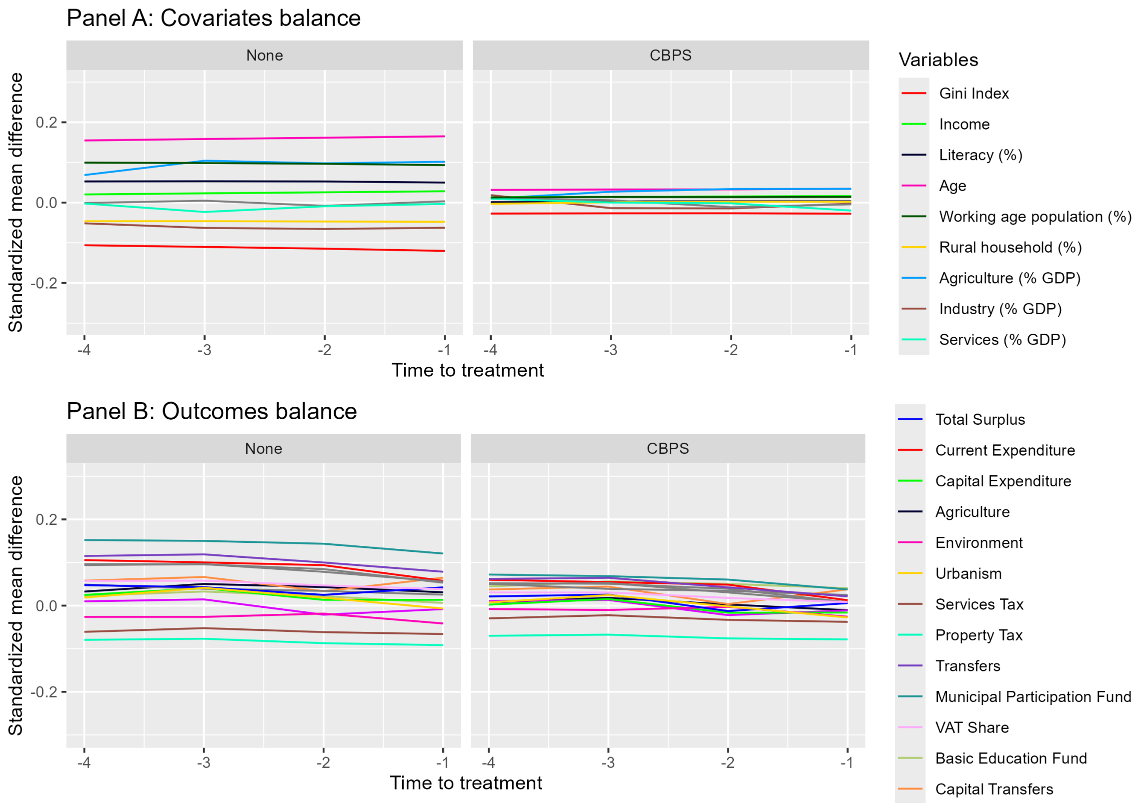
DiD estimators with staggered treatment designs) relies on the first treatment changes, and these tend not to be evenly spread across all periods when these events occur in the same places (Figure 3). Rather, they accumulate at the beginning of the panel. Second, when a municipality is impacted one more time by a hazard in the future, the contemporaneous impact of a new event will be diluted in a lead effect of the first occurrence. Since each treated unit may take different treatment paths (sequence of treated/untreated statuses) after the first treatment, each lead effect represents a weighted average of the effects of treated and untreated units, compared to control units that did not change their statuses since the beginning of the panel. Therefore, this estimator is sensitive to the chosen initial period of observation in this specific setting.

In the method proposed by Imai et al. (2023), not only the first treatment change of a unit is used as a reference point but every subsequent new treatment of the same unit is also taken into account. This is achieved by pairing each treated observation with control observations with identical treatment histories up to a specified number of lags. Then, each matched set of treated observations and its controls can be refined by applying a matching method to control differences in pre-treatment characteristics. In this study, we applied the Covariate Balancing Propensity Score (CBPS) method (Imai & Ratkovic, 2014), which tends to outperform the traditional propensity score by also minimizing covariate differences within a defined number of lags. Finally, a difference-in-difference estimator can be used to estimate both short-term and long-term average treatment effects (ATT).

In the standard form of this approach, each lead effect represents the average effect of both treated and untreated units, similar to de Chaisemartin and d'Haultfoeuille's (2024) approach. However, Imai et al.'s (2023) estimator allows researchers to define specific treatment paths for the observations. In this study, we focus solely on municipalities that experienced a disaster for two consecutive years to estimate the first lead effect. This allows for a clearer interpretation of the lead effect as a cumulative effect of being treated for two consecutive years, instead of averaging the municipalities affected for two consecutive years along with those that became untreated in the following year. Given that the effects of hazards can persist after the fact, we also calculated the average reversal effect (ART), which indicates the impact in the aftermath. This method is similar to calculating the ATT, but it utilizes treated observations as controls for the untreated ones.

In Figure 2, we can assess the quality of the matching procedure by examining the covariates and outcome variables balance for observations affected by drought and their matched sets. In Panel A, we observe that the standard differences of the covariates between treated observations and their controls decreased as expected since the CBPS minimizes the differences between groups. Moreover, even not using the lagged outcome variables in the matching method, the differences between the groups also decreased for these variables (Panel B). The variable balance for flood-affected municipalities and their control groups is similar to the drought case, so it is provided in Appendix 5.

Figure 2: Variables balance for drought-affected municipalities and their controls




Notes: The graphs show the standardized mean differences between the treated observations and their matched set without using a matching method (left) and refining through Covariate Balancing Propensity Score (CBPS) (right).

# 5 Results

Tables 5 and 6 display the results for average treatment effects (ATT) and average reversal effects (ART), representing the impact of receiving treatment and no treatment, respectively, on financial variables. For the ATT, the first column represents the contemporaneous effect (0) of every disaster occurrence, and the second column is the lead effect (1), which is the cumulative effect of a municipality being affected by a disaster in two consecutive years. The ART column displays the effects of becoming untreated (reversal), that is, not being impacted for one (+1) year after the disaster. Note that the reversal effects use treated municipalities as controls and not the same control group of untreated units used for the ATT estimation.

## 5.1 Droughts

In the first year, extreme droughts had no significant impact on municipal fiscal balance. Tax revenue is not impacted, as the non-significant decrease in service tax is offset by a marginally significant increase in IPTU tax revenues (R$0.58). This may represent some local efforts to enhance tax collection on real estate properties during drought occurrences.

The impact on transfers is generally negative, but most effects are not significant for FPM, ICMS, and Capital Transfers. However, the Basic Education Fund (FUNDEB) is significantly affected. This fund receives 20% of local and state revenues and is distributed among municipalities within each state. If the total transfers fall below a specified threshold, the federal government allocates 10% of the total subnational contribution to FUNDEB to help supplement public educational resources. This ensures that a minimum funding amount per student is maintained.

Several factors could lead to a decrease in this transfer. First, a decline in tax collection may result in reduced contributions from subnational governments to the fund. Second, a drop in student enrollment (either due to students leaving public schools or relocating to different municipalities) can decrease the transfer amounts received. It is most likely that the overall decrease is attributed to the economic slowdown, as revenues from VAT Share and Service Tax are also declining, although not significantly. In contrast, school enrollment has increased despite a decrease in population (Appendix A.3), indicating that this is not the reason for the reduction in transfer amounts.

Due to consecutive years of extreme droughts, the local finances have experienced greater stress. There is a significant decrease in the fiscal balance, mainly due to a further decrease in educational grants and service tax collection. Given that the services sector was not significantly impacted by the hazard (Appendix A.3), tax avoidance has likely increased, or tax collection efforts have been reduced.

In addition, affected municipalities shifted part of their current expenditures to capital investments in response to drought. Some of these increased expenses are in agriculture and urban development, which include the acquisition of assets such as cisterns and water trucks for storage and transportation.

Most of the reversal effects are not significant, indicating that the impacts extend at least one year after the phenomenon, such as on agriculture spending. Recall that ART is the effect of being untreated, using treated units as controls. Therefore, it builds up on the contemporaneous (0) or the first lead (1) effects. For example, if we consider the reversal effects on agriculture in a region affected by drought for one year (0.66) or two consecutive years (5.60), both become more positive (+1.03). This means that there is no apparent ATT reversal in the aftermath.

However, some effects are reversed, such as capital expenditure, though these are insignificant. The decrease in spending on assets and infrastructure seems to be linked to the financial challenges faced by municipalities, as evidenced by the negative effect on fiscal surplus and transfers.

The results have shown that expenditures and revenues are not substantially impacted in the first year of extreme drought. However, when the drought persists for a second year, the reductions in local tax revenue and transfers become apparent. In addition, municipalities tend to reallocate funds from current expenditures to essential capital expenditures for mitigation strategies, probably impacting the provision of public services in the affected area. Additionally, local governments do not engage in extra borrowing during or immediately after the drought events, indicated by nonsignificant effects.

### 5.2 Floods

In contrast to droughts, municipalities affected by floods frequently experience a significant improvement in their financial balance, primarily due to an increase in grants, whereas the impact on local tax revenues is typically insignificant during and after flood events.

The transfer impact was significantly positive, not only during disaster years (14.66 and 6.50) but also maintained a non-significant reversal effect in the subsequent year. The ICMS and FUNDEB grants were positively impacted by the extreme floods. Given that the former is allocated by the state government in accordance with local economic activity, and the impacted municipalities experienced varying effects on GDP (Appendix A.3), it is likely that the increased distribution of ICMS was a discretionary act of financial assistance carried out by the state governor.

During the flood years, the impact on FPM transfers was negative, particularly in the second year (-17.80). The allocation of this grant is determined by the size of the population, where larger populations generally receive smaller per capita amounts. However, as discussed in Subsection 3.2, there are some discontinuities between per capita distribution and the number of residents, since each municipality within a certain population range receives the same fixed amount of the FPM (Figure 4). Consequently, it is challenging to understand the underlying mechanisms affecting this grant, as lowering the number of residents can reduce the per capita amount by moving to a lower population range, yet a decrease in the population may also increase the FPM transfer received. Moreover, we cannot dismiss the possibility of a discretionary increase in the distribution of the transfer made by a higher-level official.

Within the expense functions, environmental spending is negatively impacted by extreme floods over two consecutive years (-1.44) and is positively reverted in the aftermath (0.85). Additionally, expenditure on agriculture was not significantly affected, even though it is the sector most adversely impacted by the hazard (Appendix A.3). Urban expenses are also unaffected, despite the substantial increase in capital transfer revenues in the aftermath (15.82).

In the aftermath, the effects on FPM, ICMS, and FUNDEB transfers are reversed, but there is an increase in capital transfers. This indicates that the previously positive effect on total transfers is not reversed in the subsequent year after the extreme event.

In the field of financial management, municipalities that experience flooding often see an improvement in their financial balance due to increased grants. However, the repercussions on local tax revenues during and after flood events are negligible. Specifically, the favorable impact on transfers persists at least one year after the hazard, primarily attributed to the increment in capital transfers. It is noteworthy that, despite this increase, municipalities affected by floods find their expenses for urban development and infrastructure remaining unchanged. Furthermore, local administrations typically augment their borrowing in the initial year following a natural disaster (2.15), underscoring their reliance on intergovernmental transfers for disaster relief and rehabilitation endeavors.

# 6 Conclusion

This study assessed the impact of extreme floods and droughts on local public finances. Specifically, we examined how affected municipalities fund their unforeseen natural disaster expenses and whether there is evidence of moral hazard behavior in local administrations that receive intergovernmental transfers, potentially reducing spending on costly projects aimed at preventing and mitigating future hazard damages.

The findings highlight the differing fiscal consequences of droughts and floods on Brazilian municipalities, particularly regarding the volume of grants received and the allocation of resources for future disaster mitigation. Initially, droughts may not have a significant fiscal impact, but a recurring event can lead to higher deficits and lower local tax revenues in the following year. Since there is no substantial increase in transfers, the situation often forces municipalities to reallocate current funding to capital expenditures, primarily in agriculture and urban planning. The adverse effects on fiscal balance persist for at least the first few years after, seemingly limiting further investments in drought prevention measures.

On the other hand, floods lead to better fiscal balances due to enhanced financial aid for up to two years post-disaster. However, despite the rise in capital transfers, there is no significant application for environmental and urban planning projects, which are typically utilized for flood mitigation measures like constructing retention basins, enhancing drainage systems, and increasing surface permeability in urban zones. Conversely, there has been an increase in agricultural spending and in capital expenditure after the extreme event, although the latter is insignificant. This indicates a potential moral hazard issue arising from the excessive dependence on intergovernmental transfers to manage natural disasters.

While this study provides valuable insights into the impact of natural disasters on local government finance, it is important to consider the limitations under which this study was conducted. The SPEI is a commonly used indicator for monitoring drought, but it is not frequently applied to identify floods. At least, there seems to have a high correlation between the extreme SPEI levels and the reported floods in Brazil (Table 3). In addition, heavy precipitation does not always lead to flooding as there are other contributing factors such as topography, impervious surface density, infrastructure, and proximity to bodies of water (IPCC, 2023). Furthermore, because we established SPEI thresholds to identify extreme hazards and utilized a matching method (CBPS), it's likely that the treated units are mainly being compared to "almost treated" cases of severe disasters. As a result, we might be underestimating the effects.

To simplify the interpretation of results, we chose to calculate the lead effects by including only cases where a municipality endured consecutive years of disaster. Therefore, this approach limited the number of observations available for assessing the lead effects over a prolonged period. Exploring the long-term cumulative impact of these hazards in future studies would be valuable for understanding the dynamics of local finance after a natural shock.

Our findings highlight the need for targeted fiscal policies that address the unique financial challenges posed by different types of disasters. For drought-affected municipalities, policies should focus on providing direct financial support to mitigate revenue losses. In contrast, flood-affected administrations need better incentives for the effective application of transfer aids into disaster-mitigation measures. Wildasin (2008) proposed the establishment of mandatory disaster reserves in each state, funded by contributions from the subnational governments. This approach could help alleviate soft budget constraints by shifting the financial burden from the central authority to the local and regional governments. These insights can be used to design more robust fiscal frameworks and disaster management strategies, ultimately strengthening local public finance systems in the face of increasing climate risks.

# References


Albert, C., Bustos, P., & Ponticelli, J. (2022). The Effects of Climate Change on Labor and Capital Reallocation.

Aldasoro, I., & Seiferling, M. (2014). *Vertical fiscal imbalances and the accumulation of government debt* (IMF Working Paper No. WP/14/209). Washington, D.C.: International Monetary Fund.

Ault, T. R. (2020). On the essentials of drought in a changing climate. *Science*, *368*(6488), 256–260. doi: 10.1126/science.aaz5492

Barredo, J. I. (2009). Normalised flood losses in Europe: 1970–2006. *Natural Hazards and Earth System Sciences*, *9*(1), 97–104. (Publisher: Copernicus GmbH) doi: 10.5194/nhess-9-97-2009

Belasen, A. R., & Polachek, S. W. (2008). How Hurricanes Affect Wages and Employment in Local Labor Markets. *The American Economic Review*, *98*(2), 49–53. (Publisher: American Economic Association)

Borusyak, K., Jaravel, X., & Spiess, J. (2024). Revisiting Event-Study Designs: Robust and Efficient Estimation. *Review of Economic Studies*. doi: 10.1093/restud/rdae007

Boueri, R., Monasterio, L., Mation, L. F., & Silva, M. M. (2013). Multiplicai-vos e crescei? fpm, emancipação e crescimento econômico municipal. In R. Boueri & M. A. Costa (Eds.), *Brasil em desenvolvimento 2013: Estado, planejamento e políticas públicas* (pp. 221–235). Brasília: Instituto de Pesquisa Econômica Aplicada (Ipea).

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*.

Cavalcanti, F. (2018). Voters sometimes provide the wrong incentives. the lesson of the brazilian drought industry. *Munich Personal RePEc Archive*.

de Chaisemartin, C., & d'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, 1–45.

De Chaisemartin, C., & D'Haultfœuille, X. (2023). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey. *The Econometrics Journal*, *26*(3), C1–C30. doi: 10.1093/ectj/utac017

Deryugina, T. (2017, August). The fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance. *American Economic Journal: Economic Policy*, *9*(3), 168–198. Retrieved 2023-01-07, from `https://pubs.aeaweb.org/doi/10.1257/pol.20140296` doi: 10.1257/pol.20140296

Ehrl, P. (2017). Minimum comparable areas for the period 1872–2010: An aggregation of Brazilian municipalities. *Estudos Economicos*, *47*(1), 215–229. doi: 10.1590/0101-416147182phe

Eisensee, T., & Stromberg, D. (2007). News Droughts, News Floods, and U. S. Disaster Relief. *The Quarterly Journal of Economics*, *122*(2), 693–728. doi: 10.1162/qjec.122.2.693

Escaleras, M., & Register, C. A. (2012). fiscal decentralization and natural hazard risks. *Public Choice*, *151*(1-2), 165–183. doi: 10.1007/s11127-010-9740-4

Garrett, T. A., & Sobel, R. S. (2002). *The Political Economy of FEMA Disaster Payments* (Tech. Rep.). doi: 10.20955/wp.2002.012

Gebrechorkos, S. H., Peng, J., Dyer, E., Miralles, D. G., Vicente-Serrano, S. M., Funk, C., ... Dadson, S. J. (2023). Global high-resolution drought indices for 1981–2022. *Earth System Science Data*, *15*(12), 5449–5466. doi: 10.5194/essd-15-5449-2023

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*.

Goodspeed, T. J., & Haughwout, A. F. (2012). On the optimal design of disaster insurance in a federation. *Economics of Governance*, *13*(1), 1–27. doi: 10.1007/s10101-011-0103-5

Hayes, M., Svoboda, M., Wall, N., & Widhalm, M. (2011). The Lincoln Declaration on Drought Indices: Universal Meteorological Drought Index Recommended. (Section: Bulletin of the American Meteorological Society) doi: 10.1175/2010BAMS3103.1

Imai, K., & Kim, I. S. (2021). On the use of two-way fixed effects regression models for causal inference with panel data. *Political Analysis*, *29*(3), 405–415.

Imai, K., Kim, I. S., & Wang, E. H. (2023). Matching Methods for Causal Inference with Time-Series Cross-Sectional Data. *American Journal of Political Science*, *67*(3), 587–605. doi: 10.1111/ajps.12685

Imai, K., & Ratkovic, M. (2014). Covariate balancing propensity score. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *76*(1), 243–263.

IPCC. (2023). *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (1st ed.). Cambridge University Press. doi: 10.1017/9781009157896

Jerch, R., Kahn, M. E., & Lin, G. C. (2023, March). Local public finance dynamics and hurricane shocks. *Journal of Urban Economics*, *134*, 103516. Retrieved 2023-01-07, from `https://linkinghub.elsevier.com/retrieve/pii/S0094119022000924` doi: 10.1016/j.jue.2022.103516

Kornai, J. (1979). Resource-Constrained versus Demand-Constrained Systems. *Econometrica*, *47*(4), 801–819.

Kornai, J., Maskin, E., & Roland, G. (2003). Understanding the Soft Budget Constraint. *Journal of Economic Literature*, *41*(4), 1095–1136. doi: 10.32609/0042-8736-2004-12-35-53

Kuhn, C. E., Reis, F. A., Oliveira, V. G. D., Cabral, V. C., Gabelini, B. M., & Veloso, V. Q. (2022). Evolution of public policies on natural disasters in brazil and worldwide. *Anais da Academia Brasileira de Ciências*, *94*(suppl 4), e20210869. Retrieved 2023-10-25, from `http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0001-37652022000801106&tlng=en` doi: 10.1590/0001-3765202220210869

Larreguy, H. A., & Monteiro, J. C. (2014). *Media networks and political accountability: Evidence from radio networks in brazil* (Tech. Rep.). Mimeo.

Mendes, M., Miranda, R. B., & Cosio, F. B. (2008, April). *Transferências intergovernamentais no brasil: diagnóstico e proposta de reforma* (No. 40).

Miao, Q., Abrigo, M., Hou, Y., & Liao, Y. (2022). Extreme Weather Events and Local fiscal Responses: Evidence from U.S. Counties. *Economics of Disasters and Climate Change*. Retrieved 2023-01-07, from `https://link.springer.com/10.1007/s41885-022-00120-y` doi: 10.1007/s41885-022-00120-y

Miao, Q., Shi, Y., & Davlasheridze, M. (2021). fiscal Decentralization and Natural Disaster Mitigation: Evidence from the United States. *Public Budgeting & finance*, *41*(1), 26–50. Retrieved 2023-01-25, from `https://onlinelibrary.wiley.com/doi/10.1111/pbaf.12273` doi: 10.1111/pbaf.12273

Rocha, C. A. A. (2019, September). *Brazilian federal transfers to states and municipalities: a quick reference guide* (Texto para Discussão No. 264). Brasília: Núcleo de Estudos e Pesquisas da Consultoria Legislativa, Senado Federal.

Rodden, J. (2003). Federalism and Bailouts in Brazil. In J. A. Rodden, G. S. Eskeland, & J. Litvack (Eds.), *fiscal Decentralization and the Challenge of Hard Budget Constraints* (pp. 213–248). The MIT Press. doi: 10.7551/mitpress/3021.003.0012

Roth, J., Sant'Anna, P. H., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, *235*(2), 2218–2244. doi: 10.1016/j.jeconom.2023.03.008

Skidmore, M., & Toya, H. (2013). Natural Disaster Impacts and fiscal Decentralization. *Land Economics*, *89*(1), 101–117. Retrieved 2023-01-25, from `http://le.uwpress.org/cgi/doi/10.3368/le.89.1.101` doi: 10.3368/le.89.1.101

Strobl, E. (2011). The Economic Growth Impact of Hurricanes: Evidence from U.s. Coastal Counties. *The Review of Economics and Statistics*, *93*(2), 575–589. (Publisher: The MIT Press)

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199.

Svoboda, M., Hayes, M., & Wood, D. (2012). Standardized Precipitation Index: User Guide. *Drought Mitigation Center Faculty Publications*.

Tomio, F. R. L. (2002). A criação de municípios após a Constituição de 1988. *Revista Brasileira de Ciências Sociais*, *17*, 61–89.

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, *23*(7), 1696–1718. doi: 10.1175/2009JCLI2909.1

Wildasin, D. E. (2008). Disaster Policies: Some Implications for Public finance in the U.S. Federation. *Public finance Review*, *36*(4), 497–518. doi: 10.1177/1091142107306286

# Appendices

## A.1 Natural disasters in Brazil

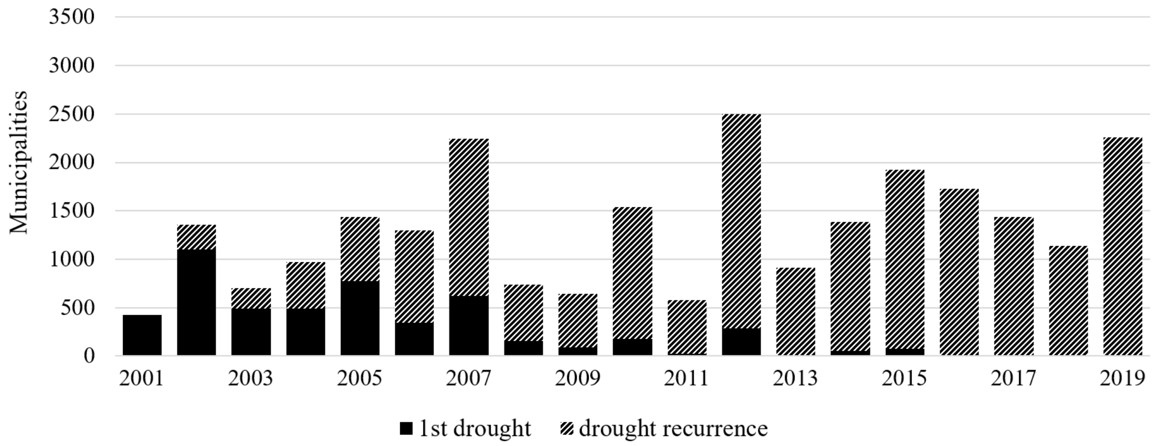
Table 7: Criteria for disaster recognition (2012)

| | **Emergency** | **Calamity** |
|---|---|---|
| **(a1) Human damages** | | |
| deaths | 1 to 9 | 10 or more |
| affected persons | up to 99 | 100 or more |
| **(a2) Material damages** | | |
| damaged public health or education facilities | 1 to 9 | 10 or more |
| damaged housing units | 1 to 9 | 10 or more |
| damaged infrastructure works | 1 to 9 | 10 or more |
| damaged public facilities for community use | 1 to 9 | 10 or more |
| **(a3) Environmental damages** | | |
| population affected by pollution and contamination of water or soil* | 5% to 10% | more than 10% |
| population affected by reduction or depletion of water* | 5% to 10% | more than 10% |
| destruction of parks, environmental protection areas or permanent preservation areas | up to 40% of the area | more than 40% of the area |
| **(b) Economic losses** | | |
| public (in essential services) | above 2.77% of net revenue | above 8.33% of net revenue |
| private | above 8.33% of net revenue | above 24.93% of net revenue |
| **(c) Local government capacity to respond and manage the crisis** | affected | exceeded |

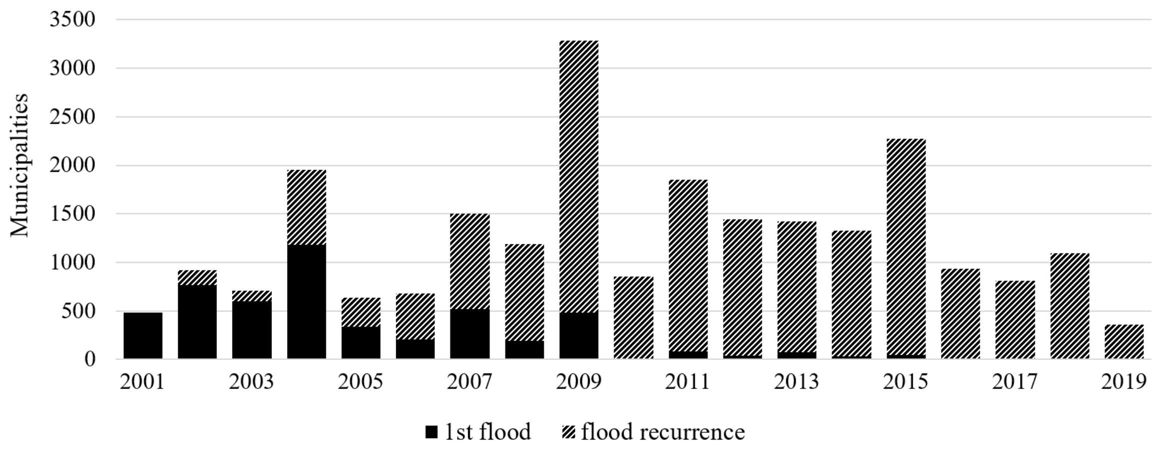
Source: Regulatory Instruction No. 1, of August 24, 2012. Notes: *Double if municipality has fewer than 10,000 inhabitants. For a recognition, the following must occur: (a) two of the three damages (human, material and environmental), (b) economic loss, and (c) affect local government capacity.

Figure 3: Distribution of the first and new disaster occurrences (2001–2019)

**Droughts**



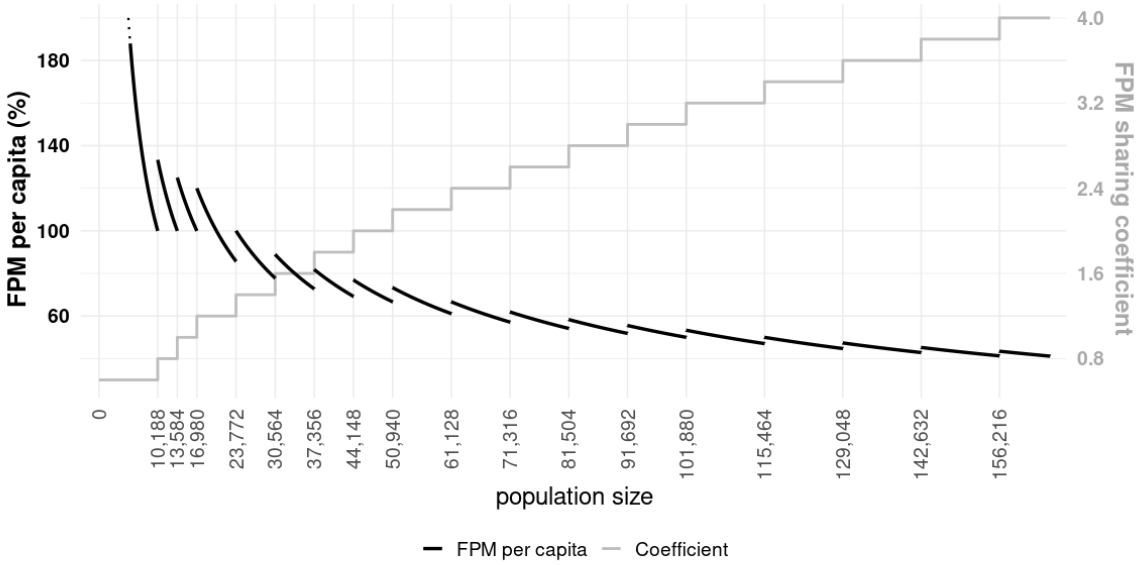

**Floods**




Notes: The figures above show the distributions of the natural disasters between 2001 and 2019. The solid black bars indicate the number of municipalities experiencing a disaster for the first time since 2001, while the hatched bars show the number of municipalities affected by the same hazard again. Adopting an empirical approach that uses the first occurrence as a reference for an event study, the contemporaneous and early lead effects predominantly capture the natural shocks that occurred at the start of the period.

## A.2 Details of Local Public Fund

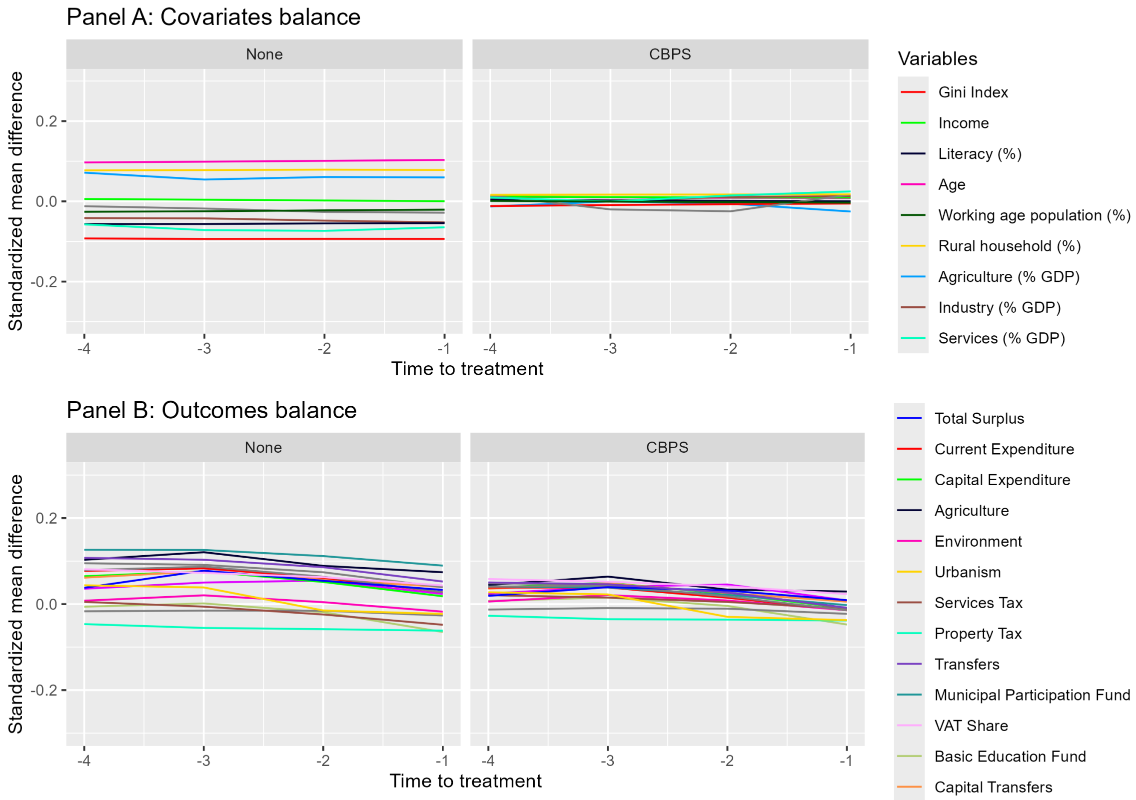
Figure 4: FPM Interior per capita and sharing coefficients by population size




Sources: Boueri et al. (2013) and Decree-Law 1,881/1981. Notes: The black lines represent the per capita transfers from the FPM received by municipalities based on their population size. The per capita value for a municipality with 10,188 residents is established at 100%. The gray line indicates the sharing coefficient (or weight) used for distributing FPM resources among the municipalities within a state.

## A.3 Effects of natural disasters on local public finance

Figure 5: Variables balance for flood-affected municipalities and their controls




Notes: The graphs show the standardized mean differences between the treated observations and their matched set without using a matching method (left) and refining through Covariate Balancing Propensity Score (CBPS) (right).

Table 8: Impact of extreme droughts on socioeconomic variables

| | SPEI $\leq -1.65$ Threshold | | |
|---|---|---|---|
| | ATT | | ART |
| **Outcome variable** | **0** | **1** | **+1** |
| Population | -49.63$^{**}$ | -111.41$^{**}$ | 86.70$^{*}$ |
| | (24.3) | (59.4) | (39.1) |
| **GDP by sector** | | | |
| Agriculture | -333.03$^{***}$ | -410.33$^{***}$ | 52.89 |
| | (31.9) | (54.0) | (48.2) |
| Industry | -91.41 | -123.59 | -23.22 |
| | (70.6) | (143.4) | (223.4) |
| Services | -41.10$^{*}$ | 11.03 | 9.53 |
| | (26.8) | (43.2) | (36.8) |
| Government | 4.21 | 42.39$^{***}$ | 23.78$^{***}$ |
| | (3.8) | (9.4) | (9.4) |
| **School enrollment** | | | |
| Basic education | 51.24$^{***}$ | 86.49$^{***}$ | -18.36 |
| | (17.6) | (23.7) | (17.4) |
| Early childhood | 4.61 | 8.66 | 7.42 |
| | (4.2) | (6.8) | (6.8) |
| Elementary & Middle | 31.19$^{***}$ | 86.03$^{***}$ | -12.76 |
| | (10.3) | (18.4) | (13.6) |
| High school | 1.84 | -10.22 | -4.52 |
| | (5.0) | (22.3) | (4.7) |
| Adult and continuing | 15.44$^{***}$ | 2.49 | -7.22 |
| | (3.8) | (6.2) | (5.1) |
| Observations | 18,018 | 5,432 | 16,789 |

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parentheses. All monetary values are in R$ per capita. ATT columns (0) and (1) represent the contemporaneous and first lead effects. ART column (+1) is the aftermath effect.

Table 9: Impact of extreme floods on socioeconomic variables

| | SPEI $\geq$ 1.83 Threshold | | |
|---|---|---|---|
| | ATT | | ART |
| **Outcome variable** | **0** | **1** | **+1** |
| Population | -82.97$^{***}$ | -48.18 | 8.08 |
| | (23.1) | (200.8) | (99.7) |
| **GDP by sector** | | | |
| Agriculture | 24.51 | -201.70$^{**}$ | -137.92$^{**}$ |
| | (24.1) | (118.8) | (63.3) |
| Industry | 42.14 | -166.16 | -53.78 |
| | (47.6) | (128.2) | (75.6) |
| Services | -12.67 | -187.26$^{***}$ | -11.12 |
| | (14.9) | (76.8) | (10.0) |
| Government | 18.30$^{***}$ | 29.59$^{***}$ | -16.44 |
| | (4.2) | (11.6) | (16.4) |
| **School enrollment** | | | |
| Basic education | -28.44 | 29.68 | -0.88 |
| | (51.8) | (65.4) | (14.7) |
| Early childhood | -2.90 | 28.31$^{***}$ | -8.20 |
| | (13.6) | (8.3) | (6.1) |
| Elementary & Middle | -28.74 | -7.10 | 9.44 |
| | (25.5) | (44.5) | (9.5) |
| High school | -2.00 | 33.66$^{***}$ | -2.72 |
| | (7.3) | (9.2) | (4.3) |
| Adult and continuing | 4.11 | -26.28 | 2.49 |
| | (5.7) | (23.2) | (5.4) |
| Observations | 17,383 | 4,161 | 18,141 |

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parentheses. All monetary values are in R\$ per capita. ATT columns (0) and (1) represent the contemporaneous and first lead effects. ART column (+1) is the aftermath effect.

Table 5: Impact of extreme droughts on local public finance

| | SPEI $\leq -1.65$ Threshold | | |
|---|---|---|---|
| | **ATT** | | **ART** |
| **Outcome variable** | **0** | **1** | **+1** |
| **Total Surplus** | -5.69 | -20.88$^{**}$ | -13.46 |
| | (7.7) | (8.7) | (17.1) |
| **Expenditures** | | | |
| Current Expenditure | -11.77$^{*}$ | -37.65$^{***}$ | 1.61 |
| | (6.0) | (11.1) | (15.0) |
| Capital Expenditure | -1.67 | 7.92 | -4.22 |
| | (3.1) | (6.3) | (6.5) |
| *by function* | | | |
| Agriculture | 0.66 | 5.60$^{***}$ | 1.03 |
| | (1.2) | (1.7) | (1.4) |
| Environment | 1.06$^{***}$ | -1.17$^{*}$ | 1.12$^{*}$ |
| | (0.4) | (0.6) | (1.0) |
| Urbanism | 3.18 | 24.14$^{*}$ | -1.85 |
| | (5.4) | (19.5) | (6.1) |
| **Revenues** | | | |
| Tax Revenue | -1.49 | -5.59 | 1.23 |
| | (1.6) | (4.7) | (3.8) |
| Services Tax (ISSQN) | -1.51 | -7.48$^{**}$ | 3.71 |
| | (1.2) | (4.8) | (3.7) |
| Property Tax (IPTU) | 0.58$^{**}$ | 0.82 | 0.14 |
| | (0.3) | (0.9) | (0.7) |
| Transfers | -13.51$^{*}$ | -48.88$^{***}$ | -11.31 |
| | (7.4) | (13.3) | (15.8) |
| Municipal Participation Fund (FPM) | -1.79 | -11.31 | -3.65 |
| | (2.9) | (7.0) | (8.5) |
| VAT Share (ICMS) | -4.33 | -5.20 | 0.19 |
| | (2.7) | (4.4) | (4.7) |
| Basic Education Fund (FUNDEB) | -9.36$^{***}$ | -21.17$^{***}$ | -0.74 |
| | (1.5) | (3.2) | (4.3) |
| Health System Transfers (SUS) | 1.29 | -6.91$^{***}$ | 7.36 |
| | (1.2) | (2.6) | (3.6) |
| Capital Transfers | -1.19 | 0.41 | -0.14 |
| | (2.0) | (3.1) | (6.2) |
| Borrowing | 0.07 | 2.69*** | -1.19 |
| | (0.6) | (1.0) | (1.1) |
| Observations | 17,485 | 5,221 | 16,262 |

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parentheses. All monetary values are in R$ per capita. ATT columns (0) and (1) represent the contemporaneous and first lead effects. ART column (+1) is the aftermath effect.

Table 6: Impact of extreme floods on local public finance

| | SPEI $\geq$ 1.83 Threshold | | |
|---|---|---|---|
| | ATT | | ART |
| **Outcome variable** | **0** | **1** | **+1** |
| **Total Surplus** | 2.35 | 16.20 | 0.63 |
| | (11.6) | (26.4) | (10.1) |
| **Expenditures** | | | |
| Current Expenditure | 12.94 | 1.95 | -11.62 |
| | (10.2) | (27.5) | (12.4) |
| Capital Expenditure | 3.61 | 0.75 | 6.88 |
| | (4.4) | (8.7) | (8.1) |
| *by function* | | | |
| Agriculture | -0.78 | -2.87 | 1.42 |
| | (1.2) | (4.1) | (2.1) |
| Environment | 0.61 | -1.44$^{*}$ | 0.85 |
| | (0.4) | (0.8) | (0.6) |
| Urbanism | 2.10 | -9.15 | -5.50 |
| | (3.1) | (9.7) | (6.4) |
| **Revenues** | | | |
| Tax Revenues | 1.23 | 3.32 | 6.00 |
| | (1.6) | (3.2) | (7.3) |
| Services Tax (ISSQN) | 1.80$^{*}$ | 2.84 | 6.43 |
| | (1.2) | (2.4) | (6.7) |
| Property Tax (IPTU) | -0.12 | -0.03 | -0.18 |
| | (0.3) | (0.5) | (0.4) |
| Transfers | 14.66$^{***}$ | 6.50 | -0.24 |
| | (7.4) | (17.0) | (13.2) |
| Municipal Participation Fund (FPM) | -3.06 | -17.80$^{***}$ | 6.20 |
| | (2.9) | (6.0) | (5.4) |
| VAT Share (ICMS) | 5.78$^{***}$ | 6.49 | -10.70$^{*}$ |
| | (2.9) | (6.1) | (5.8) |
| Basic Education Fund (FUNDEB) | 6.51$^{***}$ | 7.23$^{**}$ | -9.72$^{***}$ |
| | (1.6) | (3.5) | (3.5) |
| Health System Transfers (SUS) | 0.39 | 1.13 | -0.24 |
| | (1.2) | (3.2) | (3.1) |
| Capital Transfers | 0.08 | 5.64 | 15.82$^{***}$ |
| | (2.3) | (5.0) | (5.2) |
| Borrowing | -0.27 | -2.89$^{***}$ | 2.15$^{***}$ |
| | (0.6) | (1.3) | (0.9) |
| Observations | 16,810 | 3,985 | 17,486 |

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parentheses. All monetary values are in R$ per capita. ATT columns (0) and (1) represent the contemporaneous and first lead effects. ART column (+1) is the aftermath effect.