Impacts of natural disasters on local public finance

Evidence from droughts and floods in Brazil (2000–2019)

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Motivation

- Natural disasters can adversely affect the local economy by generating rehabilitation costs and decreasing tax revenues. (Jerch et al., 2023).
- Higher-level governments typically provide assistance through disaster and non-disaster-related transfers (Deryugina, 2017).

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- Higher-level governments typically provide assistance through disaster and non-disaster-related transfers (Deryugina, 2017).
- Unclear if local public finance will improve or deteriorate and whether budget allocations will prioritize hazard-prevention measures:
  - Natural hazards can have different impacts: droughts build effects gradually, whereas floods inflict immediate damage.
  - The amount of aid may be influenced by political interests (Garrett and Sobel, 2002) and media attention (Eisensee and Stromberg, 2007).
  - Local governments might exhibit moral hazard behavior by relying on future expected grants rather than investing in preventive measures (Goodspeed and Haughwout, 2012; Wildasin, 2008).

This paper

Examine the impact of extreme weather events on local public finance

- How local administration finance unexpected disaster expenses?
- Do governments restrict mitigation policies spending when they expect aid?
- How similar are the impacts of droughts and floods?

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- Local public finance 2000-2023 (Secretariat of National Treasury – STN)

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Method

- Difference-in-differences with matching method, which allows treatments with switching on/off behavior (Imai et al., 2023).

Preview of findings

1. **Droughts**: Municipalities receive less transfers from higher-level governments, which affects their fiscal balance and the provision of public services. This situation leads them to take on more borrowing. However, they allocate part of their resources in agricultural and environmental initiatives.

2. **Floods**: Municipalities receive more transfers and do not face financial strain. Nevertheless, these administrations do not allocate increased resources for environmental and urban development.

Preview of findings

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2. **Floods**: Municipalities receive more transfers and do not face financial strain. Nevertheless, these administrations do not allocate increased resources for environmental and urban development.

We contribute by:

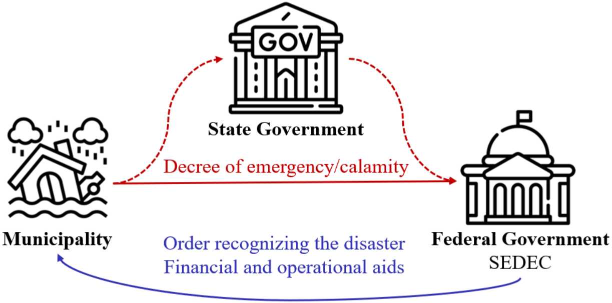
- Comparing the impact of droughts and floods on public finance, while most of the other works focus on hurricanes or floods.
- Showing evidence of moral hazard behavior due to reliance on vertical transfers in decentralized states.

Institutional Background

Civil Defense in Brazil

- In 1988, the National System for Civil Defense was established.
- The disaster report and recognition is a technical and **political** process.

▸ 2012 Recognition Criteria



- Politically important states may receive greater aids (Garrett and Sobel, 2003)
- Political alignment increases the probability to recognize decreed emergencies (Cavalcanti, 2018; Larreguy and Monteiro, 2014).
- 2007 Guide for Disasters: "(the decree) should not be made with the sole objective of resorting to the State or the Federal Government's coffers"

Treatment variables

Standard Precipitation and Evapotranspiration Index (SPEI)

- To address potential endogeneity from political interests, we used the SPEI, which is commonly used to identify droughts.
- 1981-2022 dataset by Gebrechorkos et al. (2023).
- SPEI is obtained by transforming water balance into standard deviations.

$$\text{water balance} = \text{precipitation} - \text{potential evapotranspiration (PET)}$$

SPEI	Categories
$\geq$ 1.83	extremely wet
1.43 to 1.82	very 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)

SPEI Calc
SPEI × Report

Treatment variables

Standard Precipitation and Evapotranspiration Index (SPEI)

SPEI timescales, drought types and impacts

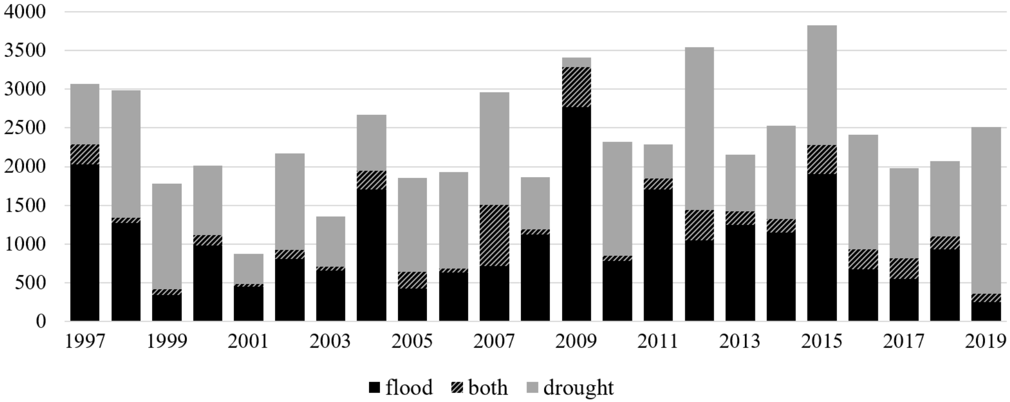
Timescale (months)	**Drought type**	**Impacts**
1	meteorological	precipitation/water balance deficits
3–6	agricultural	crop yield reduction, and soil moisture deficits
12–24	hydrological	water shortage in streams or storages (reservoirs, lakes, lagoons, and groundwater)

Sources: Svoboda et al. (2012) and IPCC (2023).

Treatment variables

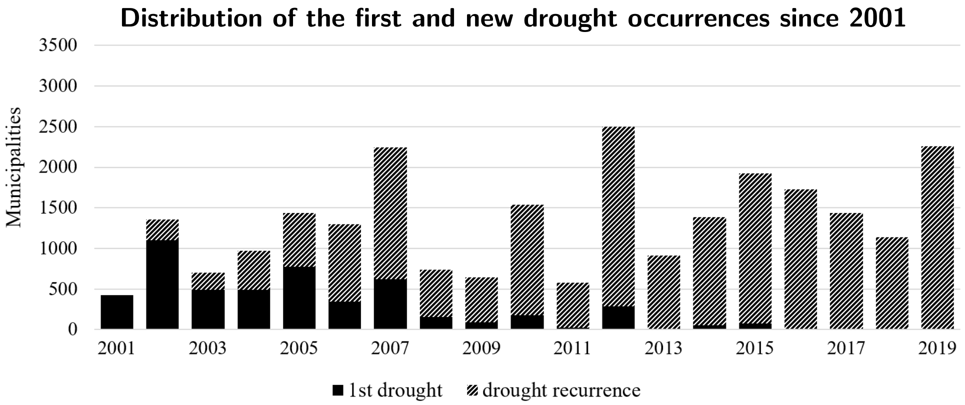
Municipalities affected by natural disasters (using SPEI)

Floods: SPEI-1 (urban areas) ≥ 1.83 **Droughts**: SPEI-3 ≤ -1.65



Identification Strategy

- Due to the recurrence of disasters in the same locations, using a staggered DiD estimator would prioritize the treatments at the beginning of the panel.



Imai, Kim and Wang's (2023) estimator

- Pairing of treated observations (i, t) with controls considering the same treatment history up to L periods before treatment.

time

units	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
$i = 1$	0	0	0	1	0	1
$i = 2$	0	0	0	0	1	1
$i = 3$	1	0	0	1	0	0
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- Restricted ATT on leads when remain treated (Interpretability $\times$ Long-term).
- For aftermath effects, we computed reversal effects (ART).

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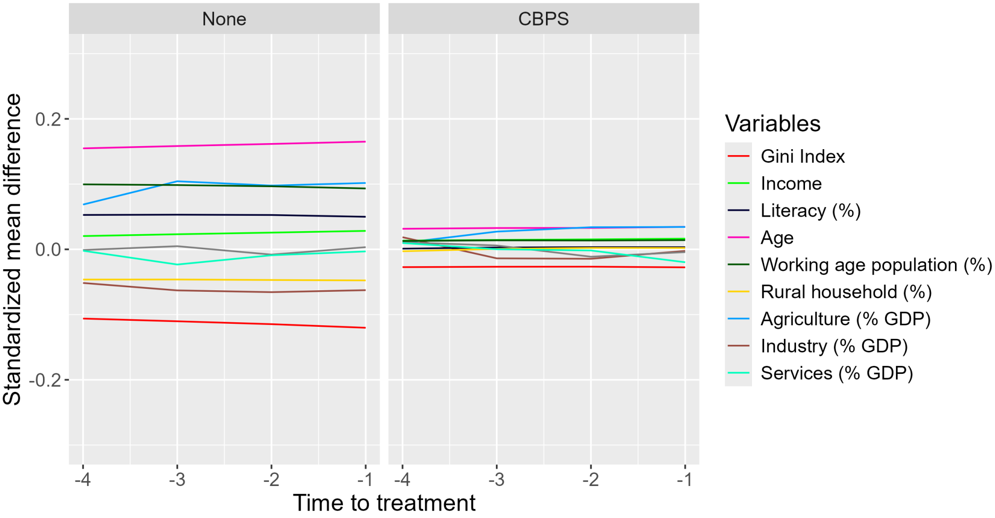
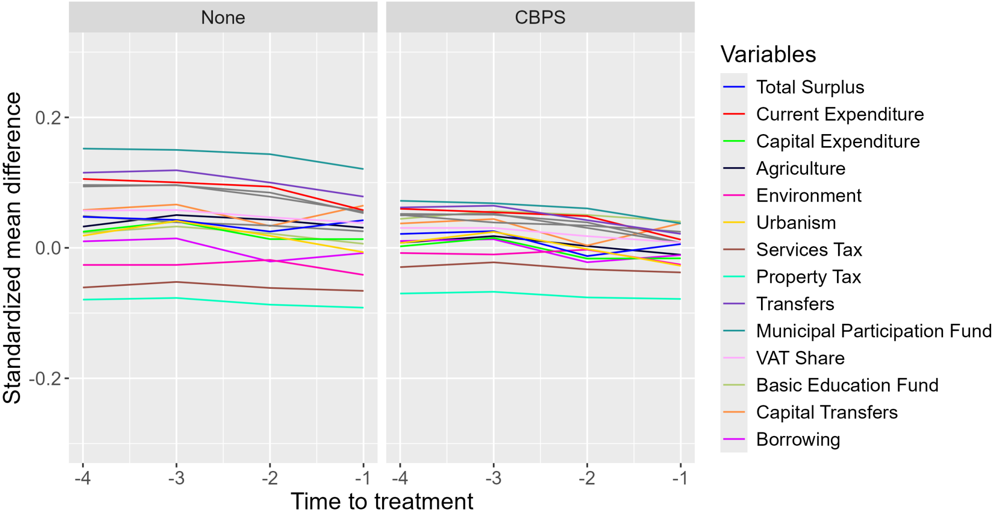
- Restricted ATT on leads when remain treated (Interpretability $\times$ Long-term).
- For aftermath effects, we computed reversal effects (ART).
- Refined control groups using Covariate Balancing Propensity Score (CBPS)
  - Matching method that directly optimizes the covariates balance.
  - More robust to misspecifications than PS (Imai and Ratkovic, 2014).

Covariates Balance for Droughts



Outcomes Balance for Droughts



Results | Droughts

Effects of droughts on local public finance

Tax/Transfer Socioeconomic

	SPEI ≤ -1.65 Threshold			
	ATT		ART	
Outcome variable	**0**	**1**	**+1**	**+2**
Total Surplus	-5.69	-20.88**	-13.46	-28.19
	(7.7)	(8.7)	(17.1)	(24.0)
Expenditures				
Current Expenditure	-11.77*	-37.65***	1.61	-35.62
	(6.0)	(11.1)	(15.0)	(24.7)
Capital Expenditure	-1.67	7.92	-4.22	-27.74*
	(3.1)	(6.3)	(6.5)	(17.9)
by function				
Agriculture	0.66	5.60***	1.03	1.86
	(1.2)	(1.7)	(1.4)	(2.5)
Environment	1.06***	-1.17*	1.12*	1.08
	(0.4)	(0.6)	(1.0)	(1.7)
Revenues				
Tax Revenue	-1.49	-5.59	1.23	-6.72
	(1.6)	(4.7)	(3.8)	(5.4)
Transfers	-13.51*	-48.88***	-11.31	-66.47
	(7.4)	(13.3)	(15.8)	(36.2)
Borrowing	0.07	2.69***	-1.19	-1.40
	(0.6)	(1.0)	(1.1)	(2.8)
Observations	17,485	5,221	16,262	10,479

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parenthesis. All monetary values are in R$ per capita. ATT columns (0) and (1) represent the contemporaneous and next year effects. ART columns (+1) and (+2) are the aftermath effects.

Results | Floods

Effects of floods on local public finance

Tax/Transfer Socioeconomic

	SPEI $\geq$ 1.83 Threshold			
	ATT		ART	
Outcome variable	**0**	**1**	**+1**	**+2**
Total Surplus	2.35	16.20	0.63	-5.53
	(11.6)	(26.4)	(10.1)	(21.5)
Expenditures				
Current Expenditure	12.94	1.95	-11.62	-37.02
	(10.2)	(27.5)	(12.4)	(51.4)
Capital Expenditure	3.61	0.75	6.88	18.07
	(4.4)	(8.7)	(8.1)	(15.0)
by function				
Environment	0.61	-1.44*	0.85	4.56*
	(0.4)	(0.8)	(0.6)	(3.4)
Urbanism	2.10	-9.15	-5.50	-3.42
	(3.1)	(9.7)	(6.4)	(12.7)
Revenues				
Tax Revenues	1.23	3.32	6.00	2.62
	(1.6)	(3.2)	(7.3)	(7.0)
Transfers	14.66***	6.50	-0.24	-22.46
	(7.4)	(17.0)	(13.2)	(57.3)
Borrowing	-0.27	-2.89***	2.15***	-3.50
	(0.6)	(1.3)	(0.9)	(4.4)
Observations	16,810	3,985	17,486	11,262

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parenthesis. All monetary values are in R$ per capita. ATT columns (0) and (1) represents the contemporaneous and next year effects. ART columns (+1) and (+2) are the aftermath effects.

Final Remarks

- We examined how municipalities affected by natural disasters manage unexpected costs and whether intergovernmental transfers discourage investment in hazard efforts.
- The findings reveal that droughts and floods have different fiscal impacts on Brazilian municipalities, especially concerning grants received and resource allocation for disaster mitigation.
- This highlights the need for targeted fiscal policies to address these unique financial challenges. Drought-affected municipalities should receive direct financial support to offset revenue losses, while flood-affected areas need better incentives to effectively apply resources for disaster mitigation.

Appendices

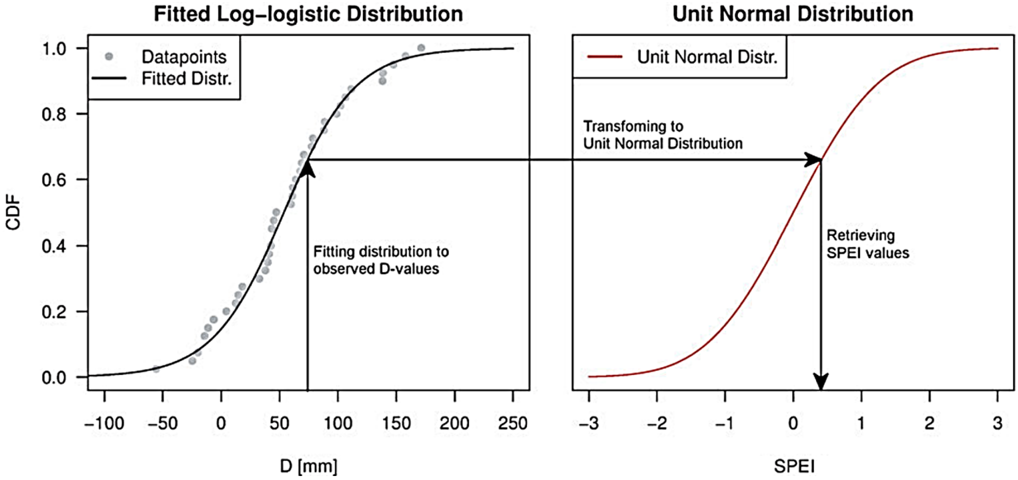
Criteria for emergency/calamity recognition (2012)

	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

*double if fewer than 10,000 inhabitants

Civil Defense

SPEI Calculation



◂ SPEI

Source: Haslinger et al. (2015)

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 classified using SPEI-3 and reported floods classified using SPEI-1 (urban). Sources: SEDEC and Gebrechorkos et al. (2023).

◂ SPEI

Effects of droughts on tax revenues and transfers

	SPEI ≤ -1.65 Threshold			
	ATT		ART	
Outcome variable	**0**	**1**	**+1**	**+2**
Revenues				
Tax Revenue	-1.49	-5.59	1.23	-6.72
	(1.6)	(4.7)	(3.8)	(5.4)
Services Tax (ISSQN)	-1.51	-7.48**	3.71	-0.75
	(1.2)	(4.8)	(3.7)	(4.3)
Property Tax (IPTU)	0.58**	0.82	0.14	-0.55
	(0.3)	(0.9)	(0.7)	(1.4)
Transfers	-13.51*	-48.88***	-11.31	-66.47
	(7.4)	(13.3)	(15.8)	(36.2)
Municipal Participation Fund (FPM)	-1.79	-11.31	-3.65	17.07
	(2.9)	(7.0)	(8.5)	(12.6)
VAT Share (ICMS)	-4.33	-5.20	0.19	-9.07
	(2.7)	(4.4)	(4.7)	(11.2)
Basic Education Fund (FUNDEB)	-9.36***	-21.17***	-0.74	2.91
	(1.5)	(3.2)	(4.3)	(8.7)
Capital Transfers	-1.19	0.41	-0.14	-38.94**
	(2.0)	(3.1)	(6.2)	(18.8)
Observations	17,485	5,221	16,262	10,479

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parenthesis. All monetary values are in R$ per capita. ATT columns (0) and (1) represent the contemporaneous and next year effects. ART columns (+1) and (+2) are the aftermath effects.

Results: Droughts

Effects of droughts on socioeconomic variables

	SPEI ≤ -1.65 Threshold			
	ATT		ART	
Outcome variable	**0**	**1**	**+1**	**+2**
Population	-49.63**	-111.41**	86.70*	101.75
	(24.3)	(59.4)	(39.1)	(124.7)
GDP by sector				
Agriculture	-333.03***	-410.33***	52.89	-161.22
	(31.9)	(54.0)	(48.2)	(308.9)
Industry	-91.41	-123.59	-23.22	-118.05
	(70.6)	(143.4)	(223.4)	(144.9)
Services	-41.10*	11.03	9.53	-263.22***
	(26.8)	(43.2)	(36.8)	(119.0)
Government	4.21	42.39***	23.78***	8.20
	(3.8)	(9.4)	(9.4)	(33.6)
School enrollment				
Early childhood	4.61	8.66	7.42	18.87*
	(4.2)	(6.8)	(6.8)	(12.4)
Elementary	31.19***	86.03***	-12.76	-96.46***
	(10.3)	(18.4)	(13.6)	(33.8)
High school	1.84	-10.22	-4.52	-6.50
	(5.0)	(22.3)	(4.7)	(9.2)
Adult and continuing	15.44***	2.49	-7.22	-35.20***
	(3.8)	(6.2)	(5.1)	(14.4)
Observations	18,015	5,431	16,785	10,920

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parenthesis. All monetary values are in R$ per capita. ATT columns (0) and (1) represents the contemporaneous and next year effects. ART columns (+1) and (+2) are the aftermath effects.

Results: Droughts

Effects of floods on tax revenues and transfers

	SPEI $\geq$ 1.83 Threshold			
	ATT		ART	
Outcome variable	**0**	**1**	**+1**	**+2**
Revenues				
Tax Revenues	1.23	3.32	6.00	2.62
	(1.6)	(3.2)	(7.3)	(7.0)
Services Tax (ISSQN)	1.80*	2.84	6.43	5.09
	(1.2)	(2.4)	(6.7)	(5.0)
Property Tax (IPTU)	-0.12	-0.03	-0.18	-0.84
	(0.3)	(0.5)	(0.4)	(1.3)
Transfers	14.66***	6.50	-0.24	-22.46
	(7.4)	(17.0)	(13.2)	(57.3)
Municipal Participation Fund (FPM)	-3.06	-17.80***	6.20	-13.47
	(2.9)	(6.0)	(5.4)	(29.9)
VAT Share (ICMS)	5.78***	6.49	-10.70*	-20.98*
	(2.9)	(6.1)	(5.8)	(12.0)
Basic Education Fund (FUNDEB)	6.51***	7.23**	-9.72***	-17.33**
	(1.6)	(3.5)	(3.5)	(8.0)
Capital Transfers	0.08	5.64	15.82***	17.96*
	(2.3)	(5.0)	(5.2)	(10.8)
Observations	16,810	3,985	17,486	11,262

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parenthesis. All monetary values are in R$ per capita. ATT columns (0) and (1) represents the contemporaneous and next year effects. ART columns (+1) and (+2) are the aftermath effects.

◂ Results: Floods

Effects of floods on socioeconomic variables

	SPEI $\geq$ 1.83 Threshold			
	ATT		ART	
Outcome variable	0	1	+1	+2
Population	-82.97***	-48.18	8.08	159.10
	(23.1)	(200.8)	(99.7)	(139.7)
GDP by sector				
Agriculture	24.51	-201.70**	-137.92**	-155.56
	(24.1)	(118.8)	(63.3)	(149.6)
Industry	42.14	-166.16	-53.78	54.82
	(47.6)	(128.2)	(75.6)	(147.8)
Services	-12.67	-187.26***	-11.12	32.72
	(14.9)	(76.8)	(10.0)	(112.7)
Government	18.30***	29.59***	-16.44	6.40
	(4.2)	(11.6)	(16.4)	(22.5)
School enrollment				
Early childhood	-2.90	28.31***	-8.20	-49.35***
	(13.6)	(8.3)	(6.1)	(18.5)
Elementary	-28.74	-7.10	9.44	40.47
	(25.5)	(44.5)	(9.5)	(30.6)
High school	-2.00	33.66***	-2.72	9.29
	(7.3)	(9.2)	(4.3)	(13.8)
Adult and continuing	4.11	-26.28	2.49	7.83
	(5.7)	(23.2)	(5.4)	(18.2)
Observations	17,379	4,160	18,141	11,831

Notes: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$. Block bootstrapped standard errors in parenthesis. All monetary values are in R$ per capita. ATT columns (0) and (1) represents the contemporaneous and next year effects. ART columns (+1) and (+2) are the aftermath effects.

◂ Results: Floods

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