Police Activity and Criminal Retaliation in Rio de Janeiro

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Final Project — Applied Economics Analysis

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Motivation

- Brazil's police activity is characterized by reactive actions instead of preemptive ones
- Rio de Janeiro's police is known for incursions into *favelas* (Monteiro, Fagundes, and Guerra 2020)
  - Death of police officers, criminals, and innocent citizens
- Anecdotal evidence suggests a circle of violence

Police Entering ”Chapadão Complex” in 2015

Source

This Project

- Research Question: Does retaliation from criminals occur after police incursions? Or do they reduce crime?

- Results:
  - **Short-Run:**
    - Event Study
    - No significant correlation in a 7-day window around an incursion
  - **Medium-Run:**
    - Regression with FEs
    - Two-week lagged effect of police incursion associated to an increase of 25% in retaliation

Outline

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Data

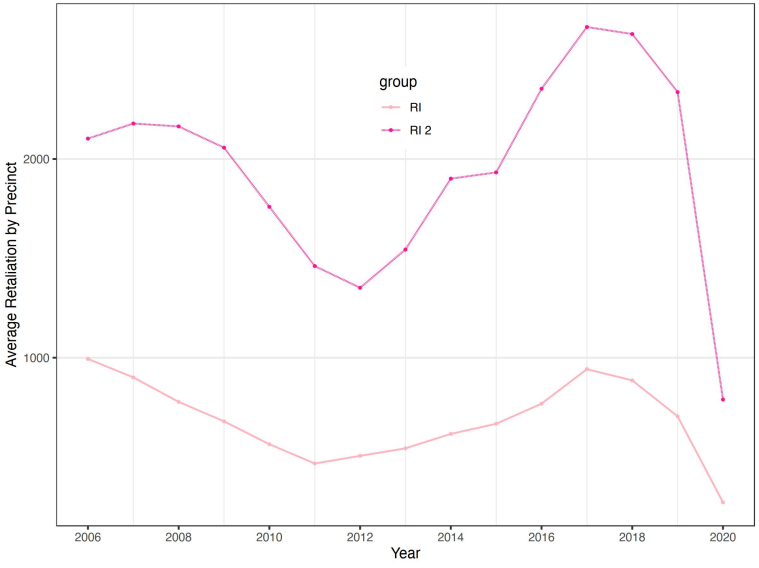
- All data comes from ISP-RJ
  - State of Rio de Janeiro's "Public Security Institute"
- Dataset:
  - Daily Crime (no longer available online)
  - Population per Precinct
  - Precinct Shapefiles

Variables of Interest

- Our two main variables are constructed based on anecdotal evidence
- We proxy police incursions by the number of police killings (Monteiro, Fagundes, and Guerra 2020)
- We construct an index of retaliation:
  - *Retaliation_Index* (RI) = *homicide* + *car_theft* + *cargo_robbery* + *car_robbery*
  - *Retaliation_Index_2* (RI_2) = *homicide* + *all_robberies* (only relevant in the appendix)
- Later we consider the per 100k inhabitants-adjusted versions of RI and RI_2
- We consider as an event whether there were police killings in a given day

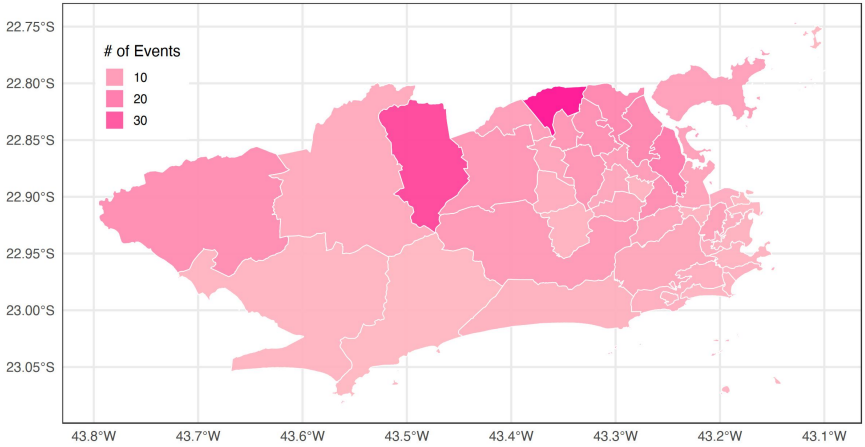
Average Number of Events per Precinct

Average Retaliation per Precinct-Year

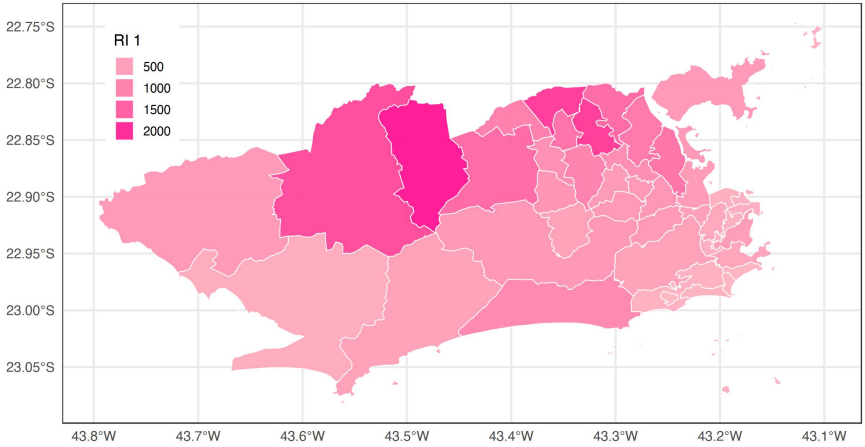


Average Number of Events per Precinct

Appendix



Average Number of Retaliation per Precinct



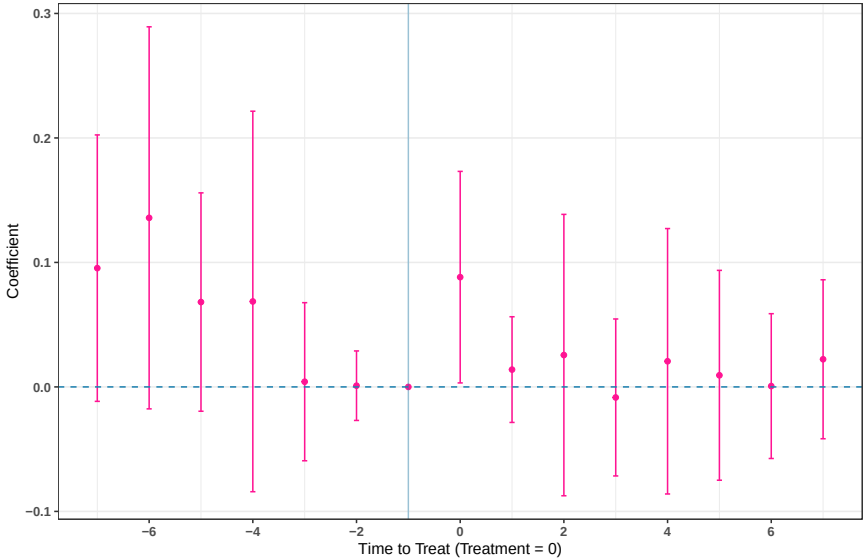
Outline

Event Study Specification

$$Retaliation_{p,d} = \beta_0 + \sum_{k=-7}^{-2} \beta_k Time\_to\_Treat_{p,k} + \sum_{j=0}^{7} \beta_j Time\_to\_Treat_{p,j} + \alpha_p + \gamma_m + \epsilon_{p,d} \quad (1)$$

- $Retaliation_{p,d}$ is the index (per 100k inhabitants) for precinct p in time to day d
- *Time_to_Treat* is a dummy for each relative day to the event
- α_p and γ_m are place and month FEs

No significant correlation in a 7-day window around an incursion



Appendix

Regression Specification

$$Retaliation_{p,w} = \beta_0 + \beta_1 Trigger_{p,w-1} + \beta_2 Trigger_{p,w-2} + \alpha_p + \gamma_y + \lambda_m + \varepsilon_{p,w} \quad (2)$$

- $Retaliation_{p,w}$ is the index (per 100k inhabitants) for precinct p in week w
- $Trigger_{p,w-i}$ is the lagged number of police killings (per 100k inhabitants) for precinct p
- α_p, γ_y and λ_m are place, year and month FEs

Trigger two weeks before is associated with a 25% increase in retaliation

	Retaliation			
	(1)	(2)	(3)	(4)
Trigger (w-1)	0.89***	-0.01	-0.36*	-0.37*
	(0.27)	(0.21)	(0.21)	(0.21)
Trigger (w-2)	4.5***	3.6***	3.3**	3.2**
	(1.3)	(1.3)	(1.3)	(1.3)
Baseline Dep. Var.	12.8	12.8	12.8	12.8
Observations	32,140	32,140	32,140	32,140
Adjusted R^2	0.01	0.50	0.51	0.51
Within Adjusted R^2		0.01	0.01	0.01
Precinct fixed effects		✓	✓	✓
Year fixed effects			✓	✓
Month fixed effects				✓

Appendix

Outline

Conclusion

- Our results suggest no short-run correlation between police incursions and retaliation
- In the medium term, this correlation appears to be stronger after two weeks
  - Although there is a small decrease after one week after an event
- Police incursions seem ineffective as a public safety policy
- Robustness exercises in the appendix corroborate our findings

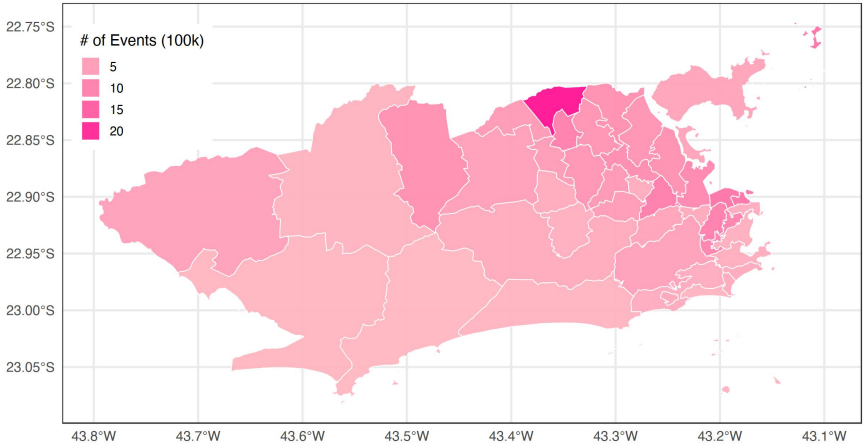
Limitations

- No causal interpretation
- Event study includes observations that overlap
- Regression lacks control variables and exogeneity

Appendix

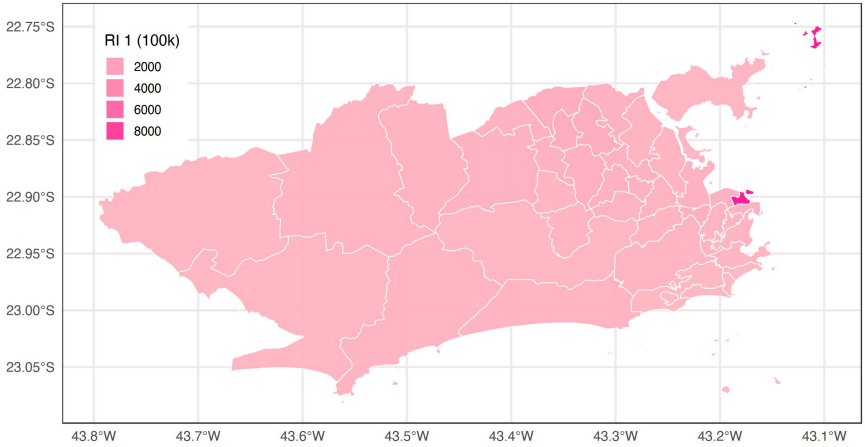
Average Number of Events (100k) per Precinct-Year

Back



Average Number of Retaliation (100k) per Precinct-Year

Back



Average Number of Retaliation per Precinct-Year

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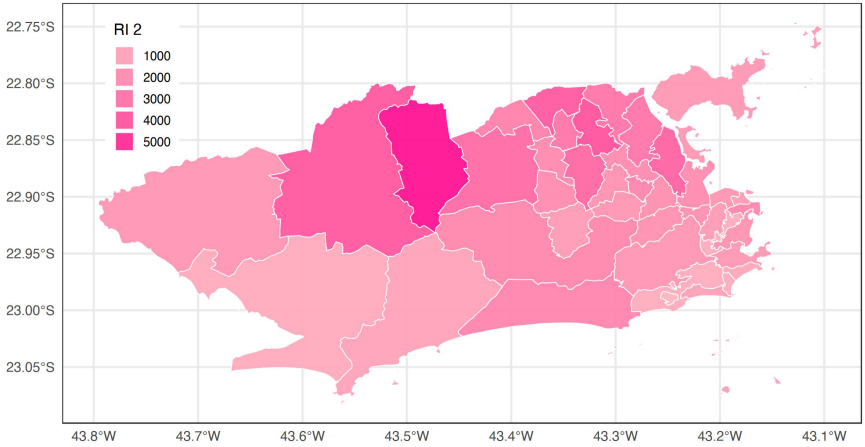
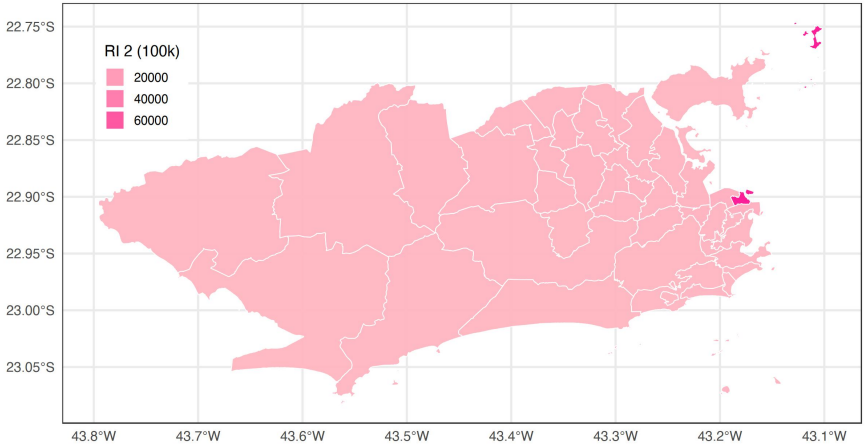


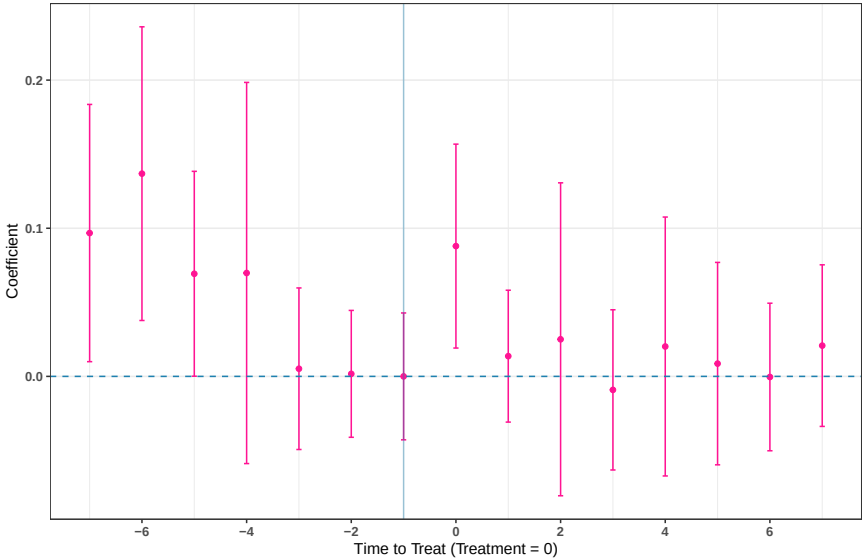
Average Number of Retaliation per Precinct-Year

Back



Event Study RI_1 without FEs

Back



Event Study RI_2 without FEs

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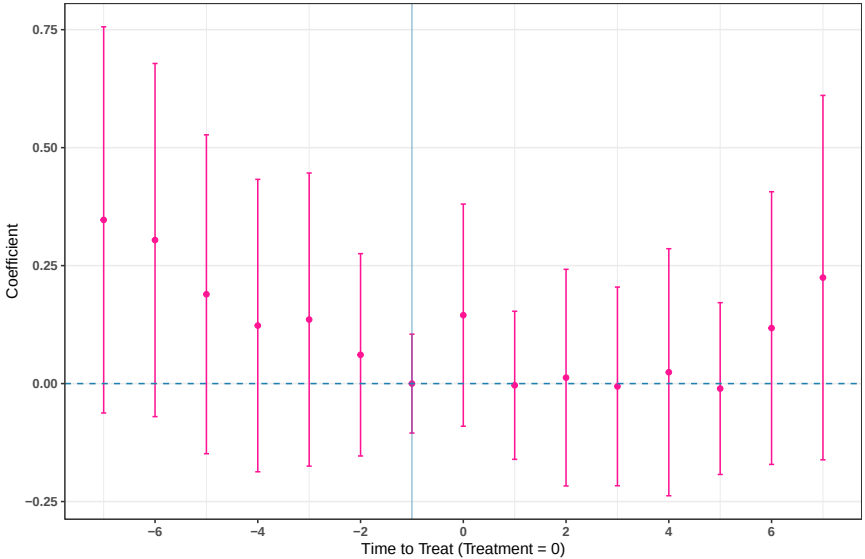
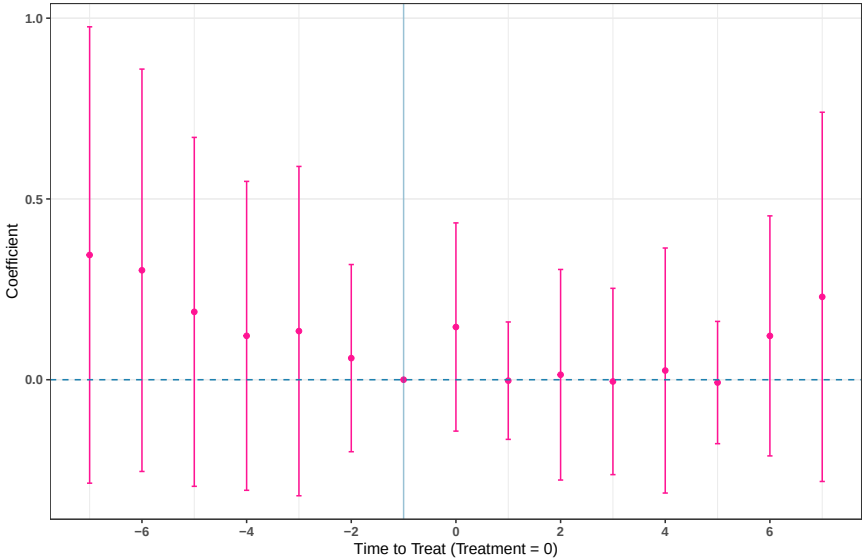


Event Study RI_2 with FEs

Back



Regression — Lags Separately

	Retaliation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trigger (w-1)	1.1***	0.89***	0.05	-0.01	-0.32	-0.36*	-0.33
	(0.34)	(0.27)	(0.23)	(0.21)	(0.23)	(0.21)	(0.23)
Trigger (w-2)		4.5***		3.6***		3.3**	
		(1.3)		(1.3)		(1.3)	
Baseline Dep. Var.	12.8	12.8	12.8	12.8	12.8	12.8	12.8
Observations	32,182	32,140	32,182	32,140	32,182	32,140	32,182
Adjusted R^2	0.0005	0.01	0.49	0.50	0.51	0.51	0.51
Within Adjusted R^2			-2.8×10^{-5}	0.01	7.1×10^{-5}	0.01	7.6×10^{-5}
Precinct fixed effects			✓	✓	✓	✓	✓
Year fixed effects					✓	✓	✓
Month fixed effects							✓

Back

Regression — Alternative Index

	Retaliation (Alternative)			
	(1)	(2)	(3)	(4)
Trigger (w-1)	8.4***	3.0***	1.4***	1.5***
	(2.6)	(0.68)	(0.36)	(0.41)
Trigger (w-2)	13.6***	8.2***	6.6**	6.6***
	(4.6)	(2.8)	(2.5)	(2.4)
Baseline Dep. Var.	64.0	64.0	64.0	64.0
Observations	32,140	32,140	32,140	32,140
Adjusted R^2	0.003	0.76	0.77	0.77
Within Adjusted R^2		0.003	0.002	0.002
Precinct fixed effects		✓	✓	✓
Year fixed effects			✓	✓
Month fixed effects				✓

Back

Regression — Lags Separately + Alternative Index

	Retaliation (Alternative)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trigger (w-1)	8.9***	8.4***	3.1***	3.0***	1.5***	1.4***	1.6***	1.5***
	(2.4)	(2.6)	(0.62)	(0.68)	(0.33)	(0.36)	(0.37)	(0.41)
Trigger (w-2)		13.6***		8.2***		6.6**		6.6***
		(4.6)		(2.8)		(2.5)		(2.4)
Baseline Dep. Var.	64.0	64.0	64.0	64.0	64.0	64.0	64.0	64.0
Observations	32,182	32,140	32,182	32,140	32,182	32,140	32,182	32,140
Adjusted R^2	0.0008	0.003	0.76	0.76	0.77	0.77	0.77	0.77
Within Adjusted R^2			0.0004	0.003	6.8×10^{-5}	0.002	7.3×10^{-5}	0.002
Precinct fixed effects			✓	✓	✓	✓	✓	✓
Year fixed effects					✓	✓	✓	✓
Month fixed effects							✓	✓

Back