

Whip or Carrot? Effect of Socio-economic Reforms on Violence

Evidence from a spatial RD in India

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Contents

- Background: Why study socio-economic reforms for mitigating violence?, Common problems, Exogenous variation....
- Methodology: Sources of data, Wrangling, Merging, Cleaning.
- Empirical strategy: Identification, Model, Controls.
- Results: State-wise, Aggregated, Placebo test.
- Conclusion: Shortcomings, Way ahead, Q/A.

Why socio-economic reforms?

Whip

Violence = ↓ f(Reforms)

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- Most instances of violence are driven by socio-economic divide. [Khanna and Zimmermann, 2017] provide two explanations:

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- Right?

Context is everything....

Carrot

Violence = $\uparrow f(\text{Reforms})$

- The story of the cat (insurgents) and the vulture (government), *Hitopadesa*.

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- The story of the cat (insurgents) and the vulture (government), *Hitopadeśa*.
- Larger resource pie explanation [ibid].
- Finding the direction of the effect is then an empirical problem.
- *neti neti*: Both approaches can be applied in varying degrees depending on the relationship in an area.

Exogenous variation

- Socio-economic reforms are implemented non-randomly.
- Reforms → Violence
- Violence → Reforms
- 2018 Revision of the SRE scheme targeted at Left-wing extremism by MHA.

Government chooses districts to be treated
↓
District boundaries become treatment cutoff
↓
Compare subdistricts along this cutoff
↓
LATE using spatial regression discontinuity

SRE scheme

- The Left-wing extremism division of MHA was created in 2006.
- SRE is an umbrella scheme enveloping several smaller reforms on Education, Health, Public Infrastructure, Roads, Communication etc.
- As of 2018, 90 districts across 11 states of India are considered LWE affected.
- Novelty of reforms introduced in 2018:
 - a. Documented evidence- Increased annual outlays, SCA scheme, USO fund etc.
 - b. Placebo test

Methodology

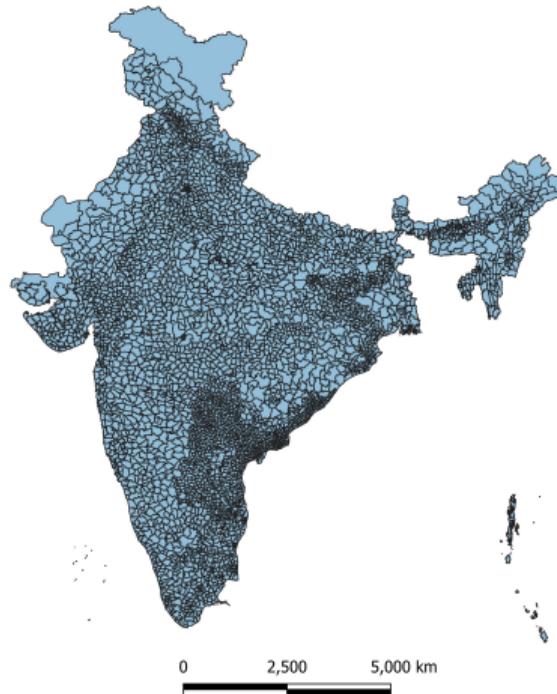
Research question

"Do the socio-economic schemes targeting LWE reduce subdistrict level violence in India?"

Sources of data:

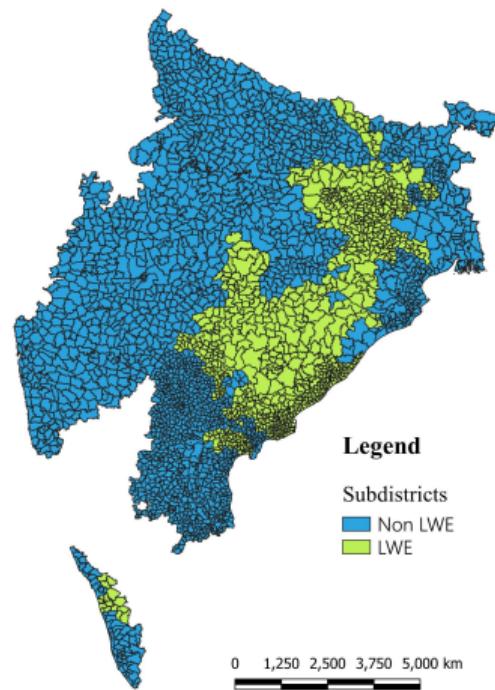
- Master shapefile- Survey of India (SoI)
- Treatment- Ministry of Home Affairs (MHA)
- Violence- Armed Conflict Location and Event Data Project (ACLED)
- Controls- Socioeconomic High-resolution Rural-Urban Geographic Platform (SHRUG)

Subdistricts shapefile



- Source: Survey of India (SoI)
- Tehsil/Taluk level administrative shapefile
- 4723 features, 5 fields, LCC_WGS84
- Upon filtering for 11, we are left with 2922 subdistricts

LWE treatment status



- MHA only provides names of Districts
- Merging areas with names is a nightmare in India- Differing spellings, Changed names...
- Jaro distance:

$$\text{Similarity} = \begin{cases} 0 & \text{if } m = 0 \\ \frac{1}{3} \left(\frac{w_1 m}{|a|} + \frac{w_2 m}{|b|} + \frac{w_3(m-t)}{m} \right) & \text{otherwise} \end{cases}$$

Here, m is the number of character matches, t is the number of transpositions, $|a|$ is the number of characters in string a and w_i are weights summing to 3.

Background
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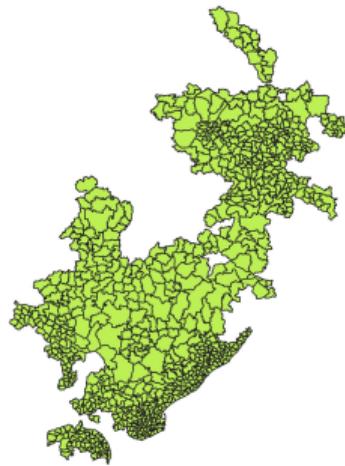
Methodology
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Empirical strategy
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Results
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Conclusion
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Cutoff



Background
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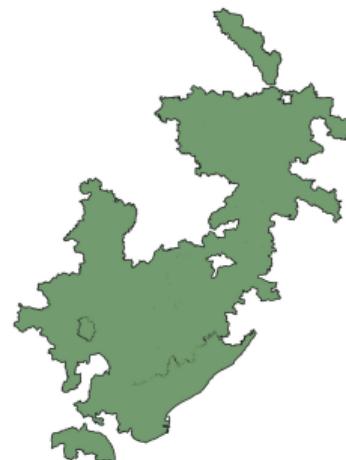
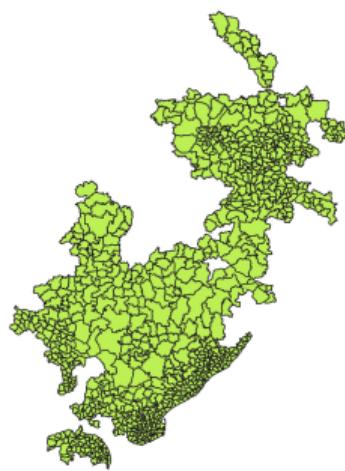
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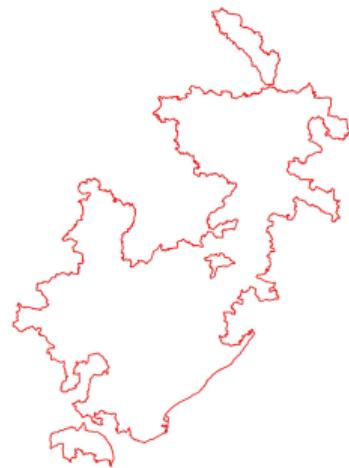
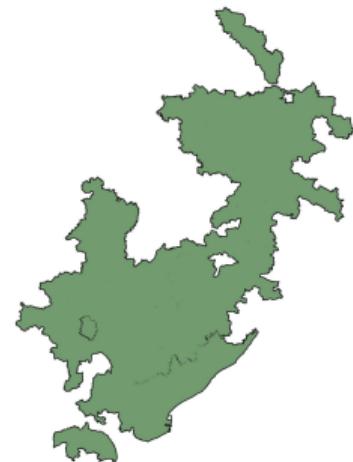
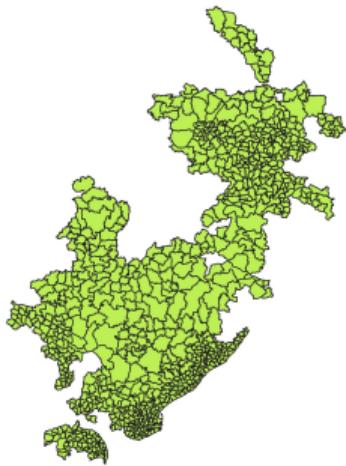
Methodology
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Empirical strategy
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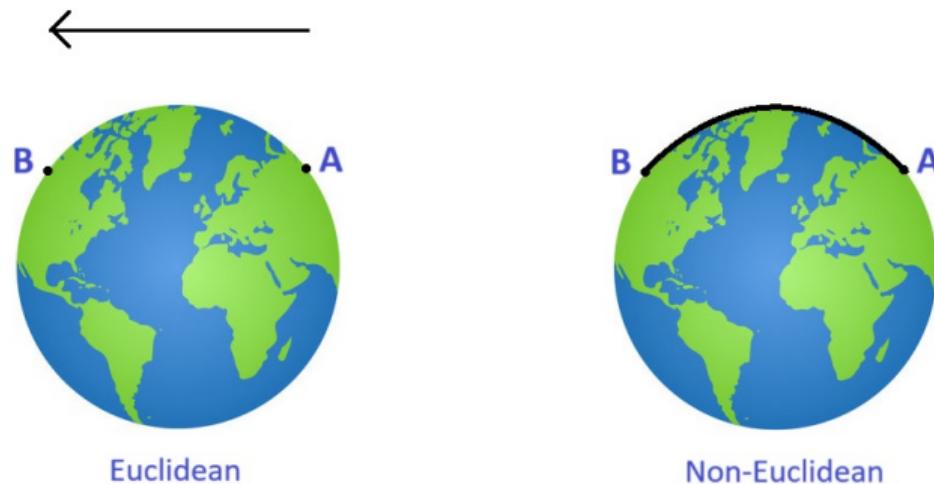
Results
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Conclusion
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Cutoff

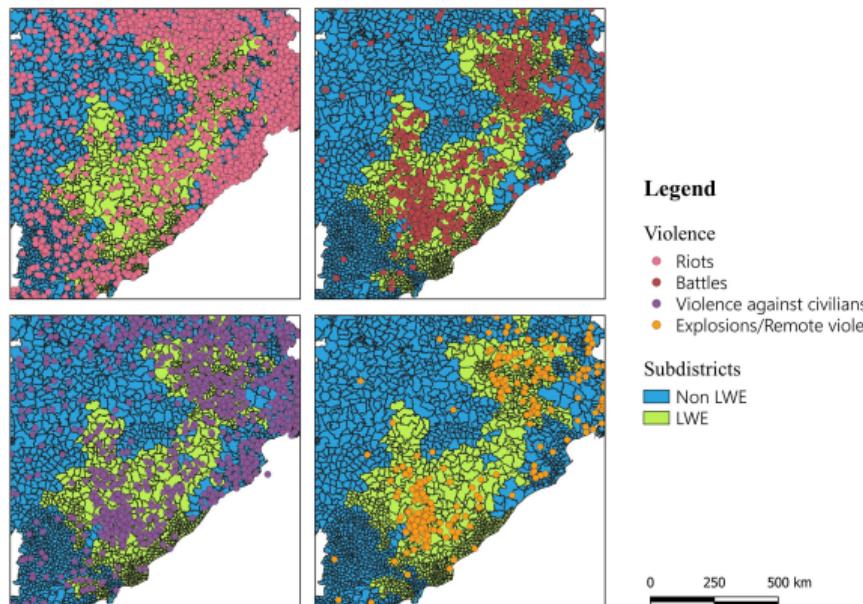


Distance to cutoff



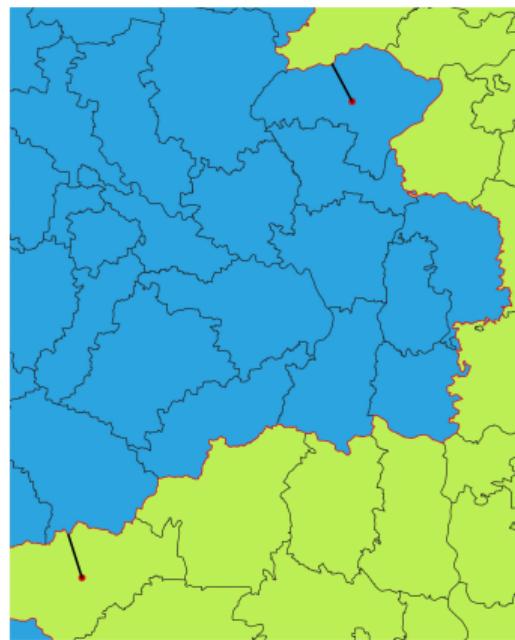
- 'Distance to cutoff' is the perpendicular distance from centroids of subdistricts to the cutoff boundary. +ve for treated and -ve for control.

Violence

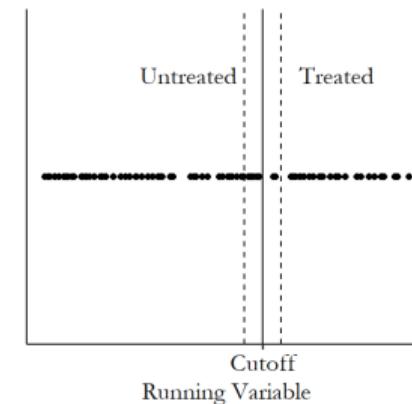


- Source: ACLED, 2016-23
- Only riots is testable
- Not filtered for cause/agent (Ex-IND1340)
- Outcome is violence and not LWE specific violence

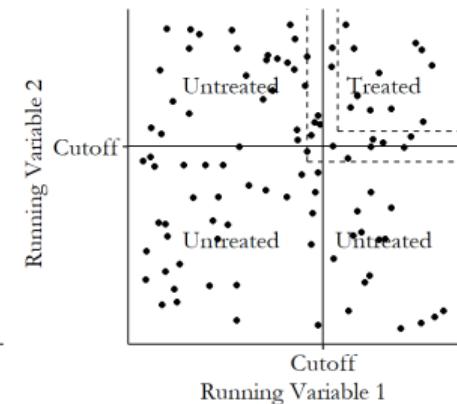
Why controls?



(a) One Running Variable

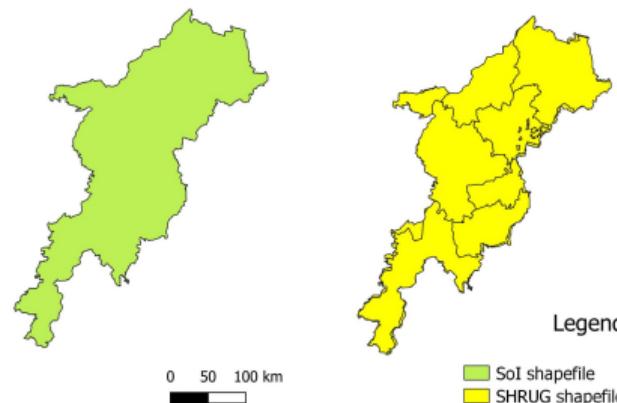


(b) Multiple Running Variables



Source: The Effect, Nick Huntington-Klein

Controls



- Source: SHRUG, PC01 and PC11
- Extrapolation:

$$\text{Growthrate}_{ij} = \frac{PC11_{ij} - PC01_{ij}}{PC01_{ij}} * 100$$

$$AGR_{ij} = \frac{\text{Growthrate}_{ij}}{10}$$

$$PC18_{ij} = PC11_{ij} \left(1 + \frac{AGR_{ij}}{100}\right)^7$$

- Forest Cover, [Ghatak and Eynde, 2017]

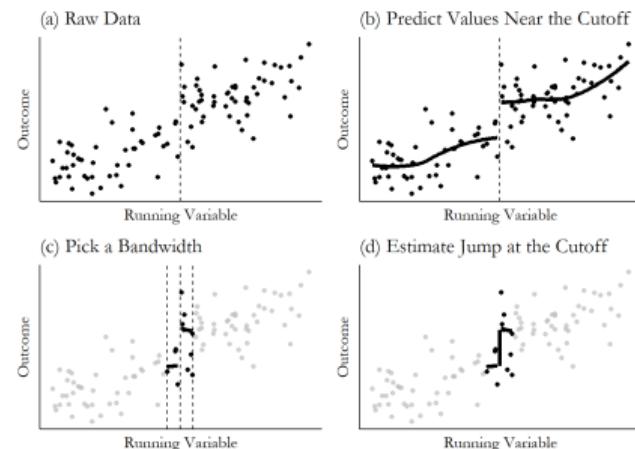
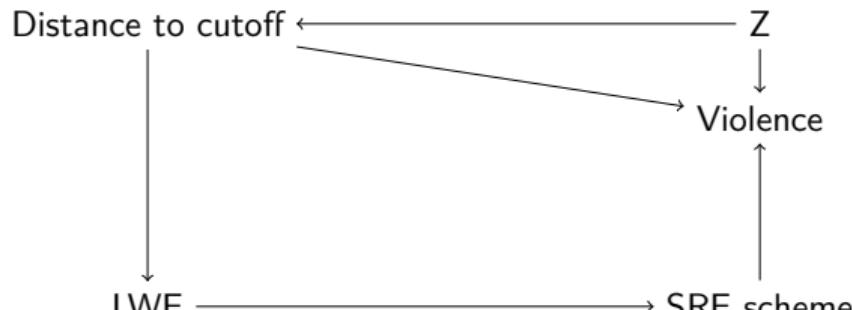
S. No	Controls	Description
1.	pc18_sc_share	Scheduled castes population share
2.	pc18_st_share	Scheduled tribes population share
3.	pc18_lit_share	Literate population share
4.	pc18_rural_share	Rural population share
5.	pc18_work_share	Working population share
6.	pc18_forest_share	Forest cover share

Data cleaning

- Remove NAs and Infs
- Winsorize top and bottom 5%
- Divide distances to cutoff by 1000 to get kms

Variable	N	Mean	St. Dev.	Min	Max
d2c_18	2,527	-107.444	161.875	-664.832	169.909
pc18_sc_share	2,527	16.841	7.929	3.494	32.510
pc18_st_share	2,527	18.185	24.451	0.098	82.164
pc18_lit_share	2,527	66.757	8.614	51.963	83.306
pc18_rural_share	2,527	86.155	19.955	33.346	100.000
pc18_work_share	2,527	46.501	8.199	30.829	59.048
pc18_forest_share	2,527	11.739	14.597	0.000	50.419

Identification



Source: The Effect, Nick Huntington-Klein

Background
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Methodology
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Empirical strategy
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Results
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Conclusion
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Model

Linear

$$riots_{post18} = \beta_0 + \beta_1 L_i + \beta_2 D_i + \beta_3 L_i D_i + \mu_i$$

Model

Linear

$$\text{riotspost18}_i = \beta_0 + \beta_1 L_i + \beta_2 D_i + \beta_3 L_i D_i + \mu_i$$

β_1 is the coefficient of interest.

Model

Linear

$$riots_{post18i} = \beta_0 + \beta_1 L_i + \beta_2 D_i + \beta_3 L_i D_i + \mu_i$$

β_1 is the coefficient of interest.

2nd order polynomial

$$riots_{post18i} = \beta_0 + \beta_1 L_i + \beta_2 D_i + \beta_3 D_i^2 + \beta_4 L_i D_i + \beta_5 L_i (D_i)^2 + \mu_i$$

Model

Linear

$$\text{riots}_{\text{post}18i} = \beta_0 + \beta_1 L_i + \beta_2 D_i + \beta_3 L_i D_i + \mu_i$$

β_1 is the coefficient of interest.

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Following the recommendations of [Gelman and Imbens, 2019], I do not check for higher order polynomials greater than two.

rdrobust

- Bias correction
- MSE optimised bandwidth selection
- Triangularly weighted kernel
- Heteroskedasticity robust standard errors
- Controls
- Restricting geographical area under study

Estimating model with controls

$$riots_{post18}is = \beta_0 + \beta_1 L_i + \beta_2 D_i + \beta_3 L_i D_i + X_i \gamma + \lambda_s + \mu_i$$

Main RD estimates

Table: State-wise Bias-corrected Robust RD Estimates

	Estimate	95% CI	Std. Error	Robust P-Value	Obs	Eff. Obs	Bandwidth	Covs
ANDHRA PRADESH	0.217	[−0.415, 0.849]	0.322	0.500	635	324	53.525	Yes
ANDHRA PRADESH	0.172	[−0.672, 1.016]	0.431	0.689	635	276	34.799	No
BIHAR	4.729	[−44.435, 53.893]	25.084	0.850	79	27	13.610	Yes
BIHAR	9.501	[−13.902, 32.904]	11.940	0.426	79	36	19.468	No
CHHATISGARH	-3.552	[−5.282, -1.822]	0.883	0.0001	117	30	14.651	Yes
CHHATISGARH	-1.412	[−3.512, 0.687]	1.071	0.187	117	32	16.075	No
JHARKHAND	0.941	[−0.503, 2.385]	0.737	0.201	256	58	11.552	Yes
JHARKHAND	0.750	[−0.626, 2.126]	0.702	0.285	256	68	14.457	No
KERALA	2.700	[−45.900, 51.300]	24.796	0.913	61	13	12.488	Yes
KERALA	14.533	[−40.786, 69.851]	28.224	0.607	61	11	11.379	No
MADHYA PRADESH	-2.205	[−6.349, 1.939]	2.115	0.297	259	24	36.846	Yes
MADHYA PRADESH	-3.026	[−11.596, 5.545]	4.373	0.489	259	22	32.865	No
MAHARASHTRA	-1.031	[−2.272, 0.209]	0.633	0.103	329	33	29.596	Yes
MAHARASHTRA	-1.643	[−3.477, 0.191]	0.936	0.079	329	29	25.233	No
ODISHA	-6.024	[−10.725, -1.323]	2.398	0.012	89	36	22.268	Yes
ODISHA	-3.066	[−7.914, 1.783]	2.474	0.215	89	36	23.332	No
TELANGANA	-0.024	[−0.845, 0.797]	0.419	0.954	429	160	25.251	Yes
TELANGANA	-0.086	[−1.016, 0.845]	0.475	0.857	429	170	27.715	No
UTTARPRADESH	-5.811	[−12.568, 0.946]	3.448	0.092	245	54	65.202	Yes
UTTARPRADESH	-6.571	[−18.715, 5.574]	6.196	0.289	245	52	60.551	No

- Catch-up effect
- Rollout and/or focused treatment
- Violence as a proxy

Aggregated RD estimate

Table: Aggregated Bias-corrected Robust RD Estimates

	Estimate	95% CI	Std. Error	Robust P-Value	Obs	Eff. Obs	Bandwidth	Covs
LWE STATES	-0.471	[-1.187, 0.245]	0.365	0.197	2527	1194	63.942	Yes
LWE STATES	-0.209	[-1.364, 0.947]	0.590	0.724	2527	1154	59.723	No

Notes. Standard errors are clustered by state.

Placebo test

Table: Placebo Test

Outcome variable: Total riots before 2018 (2016 to 2017)

	Estimate	95% CI	Std. Error	Robust P-Value	Obs	Eff. Obs	Bandwidth	Covs
CHHATISGARH	-0.068	[-1.159, 0.023]	0.046	0.142	117	32	16.280	Yes
ODISHA	-0.326	[-1.602, 0.949]	0.651	0.616	89	40	26.840	Yes

Notes. Standard errors are heteroskedasticity robust.

Conclusion

- I find that violence post 2018 is lower by approximately 4 events in Chhattisgarh and 6 events in Odisha for the treated subdistricts
- Intriguing case of Jharkhand
- Shortcomings: Filtering for LWE, Non-euclidean distance, Two-running variable approach
- Way forward: Village/Town level, Alternate sources of Violence

Fin.

Thank You