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

Evidence from a spatial RD in India

Nandish Patel

Ahmedabad University

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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 $= \downarrow$ f(Reforms)

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- Right?

Context is everything....

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- 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 $\rightarrow$ Violence
- Violence $\rightarrow$ Reforms
- 2018 Revision of the SRE scheme targeted at Left-wing extremism by MHA.

Government chooses districts to be treated

$\downarrow$

District boundaries become treatment cutoff

$\downarrow$

Compare subdistricts along this cutoff

$\downarrow$

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

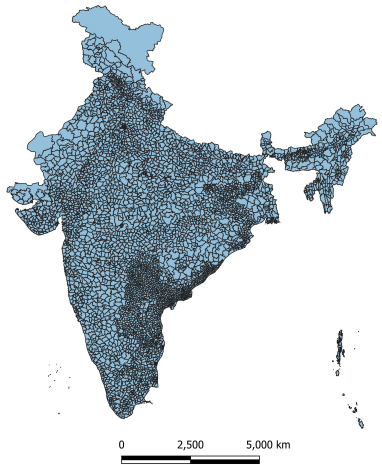
Research question

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

Sources of data:

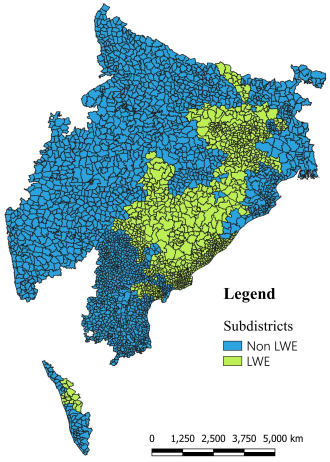
- Master shapefile- Survey of India (SoI)
- Treatment- Ministry of Home Affairs (MHA)
- Violence- Armed Conflict Location and Event Data Project (ACLED)
- Controls- Socioeconomic High-resolution Rural-Urban Geographic Platform (SHRUG)

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

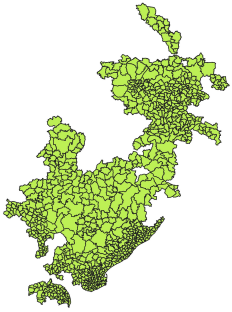


- MHA only provides names of Districts
- Merging areas with names is a nightmare in India- Differing spellings, Changed names...
- Jaro distance:

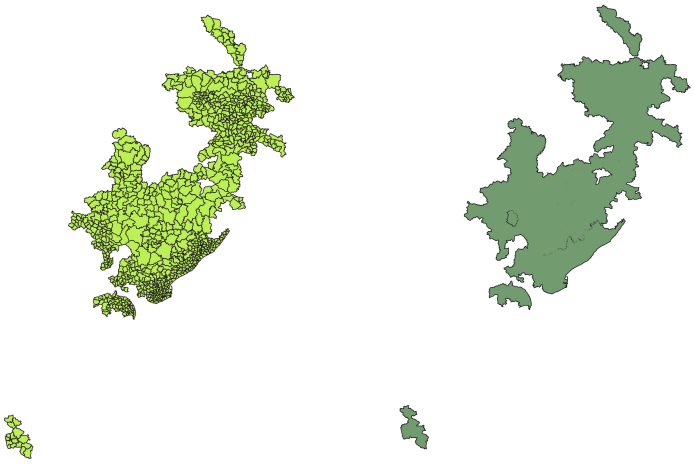
$$\text{Similarity} = \begin{cases} 0 & \text{if } m = 0 \\ \frac{1}{3}\left(\frac{w_1 m}{|a|} + \frac{w_2 m}{|b|} + \frac{w_3(m-t)}{m}\right) & \text{otherwise} \end{cases}$$

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.

Cutoff



Cutoff



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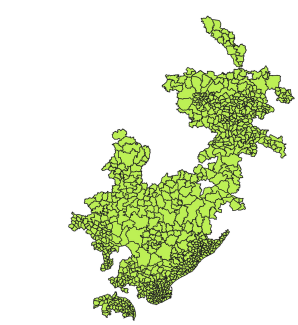
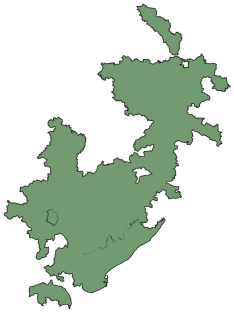
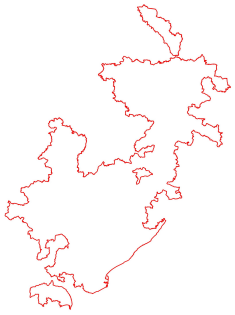
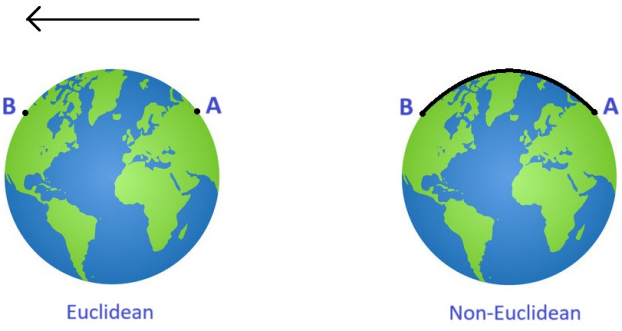




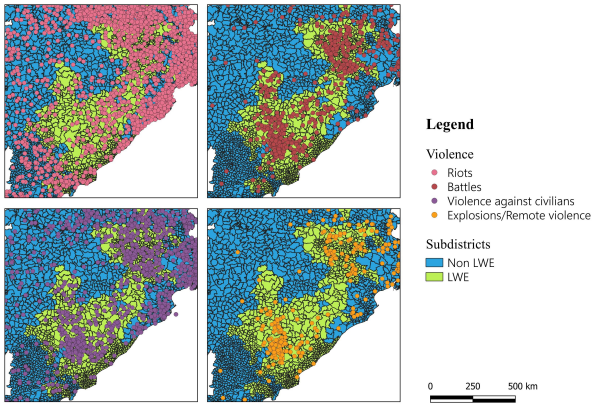


Distance to cutoff



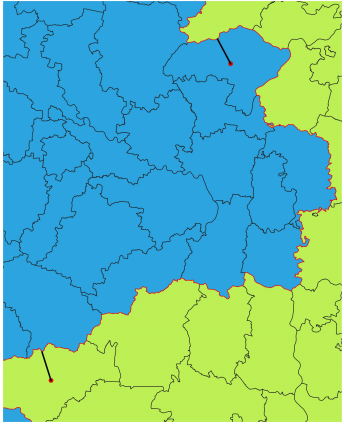
- 'Distance to cutoff' is the perpendicular distance from centroids of subdistricts to the cutoff boundary. +ve for treated and -ve for control.

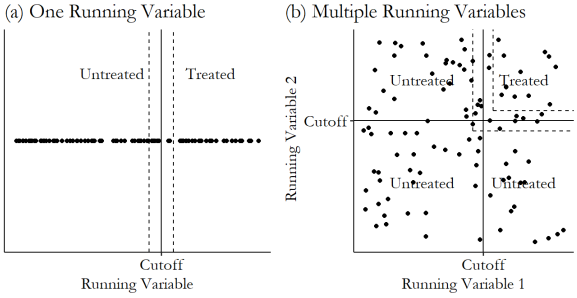
Violence



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

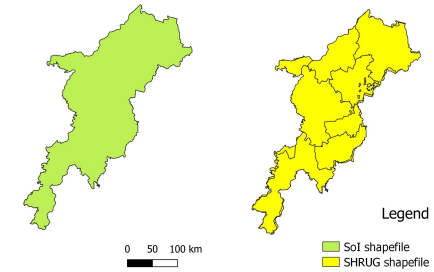
Why controls?





Source: The Effect, Nick Huntington-Klein

Controls



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

- Source: SHRUG, PC01 and PC11
- Extrapolation:

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

$$\text{AGR}_{ij} = \frac{Growthrate_{ij}}{10}$$

$$\text{PC18}_{ij} = PC11_{ij}\left(1 + \frac{AGR_{ij}}{100}\right)^{7}$$

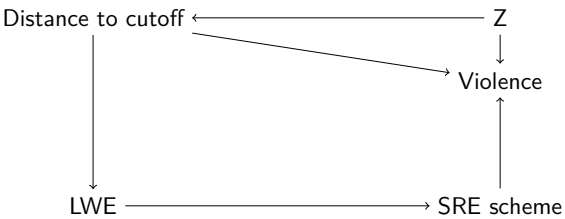
- Forest Cover, [Ghatak and Eynde, 2017]

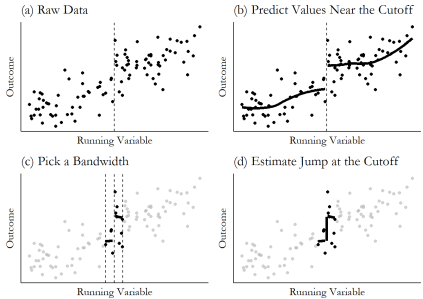
Data cleaning

- 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

Model

Linear

$$riotspost18_i = \beta_0 + \beta_1 L_i + \beta_2 D_i + \beta_3 L_i D_i + \mu_i$$

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β_1 is the coefficient of interest.

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2nd order polynomial

$$riotspost18_i = \beta_0 + \beta_1 L_i + \beta_2 D_i + \beta_3 {D_i}^2 + \beta_4 L_i D_i + \beta_5 L_i (D_i)^2 + \mu_i$$

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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

$$riotspost18_{is} = \beta_0 + \beta_1 L_i + \beta_2 D_i + \beta_3 L_i D_i + X_i\gamma + \lambda_s + \mu_i$$

Main RD estimates

Table: State-wise Robust RD Estimates

	Estimate	95% CI	Std. Error	Robust P-Value	Obs	Eff. Obs	Bandwidth	Covs
ANDHRA PRADESH	2.125	[−0.772, 5.021]	1.478	0.151	635	116	13.515	Yes
ANDHRA PRADESH	1.382	[−1.813, 4.577]	1.630	0.397	635	128	15.345	No
BIHAR	14.087	[−128.410, 156.585]	72.704	0.846	79	11	7.035	Yes
BIHAR	−39.645	[−110.808, 31.518]	36.308	0.275	79	5	5.643	No
GUJARAT	3.702	[−14.711, 22.115]	9.394	0.694	201	47	36.846	Yes
GUJARAT	−0.989	[−24.325, 22.346]	11.906	0.934	201	47	34.969	No
JHARKHAND	**-18.790**	**[-35.527,-2.054]**	**8.539**	**0.028**	**256**	**17**	**4.398**	**Yes**
JHARKHAND	−22.381	[−40.013, −4.749]	8.996	0.013	256	43	6.602	No
MADHYA PRADESH	3.868	[−4.513, 12.250]	4.277	0.366	259	77	24.041	Yes
MADHYA PRADESH	6.142	[−2.170, 14.454]	4.241	0.148	259	72	21.989	No
MAHARASHTRA	0.746	[−17.722, 19.214]	9.423	0.937	329	53	15.824	Yes
MAHARASHTRA	−2.357	[−28.844, 24.129]	13.514	0.862	329	54	16.327	No
MIZORAM	8.251	[1.925, 14.578]	3.228	0.011	16	15	124.220	Yes
MIZORAM	23.682	[14.480, 32.884]	4.695	0.000	16	15	124.220	No
RAJASTHAN	29.610	[−25.449, 84.670]	28.092	0.292	230	45	17.098	Yes
RAJASTHAN	31.702	[−26.159, 89.562]	29.521	0.283	230	63	25.969	No
TELANGANA	2.924	[−17.674, 23.522]	10.509	0.781	429	23	5.165	Yes
TELANGANA	−13.303	[−50.241, 23.636]	18.847	0.480	429	21	4.833	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
ALL STATES	1.829	[−1.561, 5.220]	1.730	0.290	3456	889	20.572	Yes
ALL STATES	−1.916	[−17.619, 13.787]	8.012	0.811	3456	1194	30.659	No

Notes. Standard errors are clustered by state.

Placebo test

Table: Placebo Test

Outcome variable: PM2.5 before policy implementation

	Estimate	95% CI	Std. Error	Robust P-Value	Obs	Eff. Obs	Bandwidth	Covs
JHARKHAND	-17.297	$[-36.163, 1.568]$	9.626	0.072	256	29	5.261	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

Thank You