Crime rate in India: Impact of social, economic and climatic factors

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Outline of the paper

- Motivation
- Data sources and variables
- Methods
- Results
- Analysis
- Conclusion

Motivation

- Study of crime and its determinants - matter of global concern
- What compels individual to inflict harm on another and how can it be prevented-multiple disciplines (Collins, 2009)
- Focus-inter sectional analysis-violence and race, class, gender, sexual orientation and work (Conwill, 2010; Farrington et al., 2003; Shields, 2008)
- Prevention- government, public health and criminal justice (Middleton, 1998; Moore, 1993)

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What are the circumstances in which predatory criminal acts are carried out?

Theory: Macro-Level Predictors

- Criminologists- micro-level question of why individuals break the law
  - individual-unit of analysis, explored predictors of individual criminal behaviour (Hirschi, 1969)
  - Macro-characteristics of neighbourhoods, census tracts, cities,states, nations -affects crime
  - Social disorganization theory-Shaw and McKay (1942)
- Economists
  - crime-activity undertaken as any other economic activity
  - potential criminal- compare benefits and costs-alternative forms of action
  - deterrence hypothesis-severity of punishment- reduces crime, empirically tested (Becker 1968; Ehrlich, 1972).

Theory: Macro-Level Predictors

- Conditions for crime
  - Presence of motivation to commit crime ‘Motivated offenders’
  - Targets-Individuals or property ‘Suitable targets’
  - Circumstances-conducive conditions for crime ‘Absence of capable guardians’ (Cohen and Felson, 1979)
- Unemployment and crime- two effects on crime
  - Increased motivation rooted in economic hardship-increases crime
  - Guardianship-decreases crime (Cantor and Land 1985)
- Empirically tested Andresen (2012), crime-spatial perspective (Brain and Prieto, 2021)

Theory: Macro-Level Predictors

- Inequality and violent crime
  - Socioeconomic inequality between races, economic inequality/poverty, relative deprivation (Blau and Blau, 1982)
  - Income inequality-increased homicide rates, burglary (Fajnzylber et al.2002; Choe, 2008), Geographical differences-predictor of crime at cross country level, Kim et al, (2020)-depends on sample composition
  - Inequality-no effect on property crime but-on violent crime in USA (Kelly 2000)
  - Inequalities in power, economic or political- crime, Inequality positively related to CAW-India (Iyer et al., 2012; Shoukry Rashad et al, 2019; Chowdhury et al, 2022)

Factors predicting crime

- Socio economic, institutional, climatic, demographic, macro-economic ecological (Ellis et al, 2009)
  - personal, situational, and cultural influences-GBV (Heise, 1998)
  - rainfall and temperature-violent and property crimes, riots, civil war (Agnew, 2012; Hu et al; 2017; Blakeslee and Fishman, 2018; Baysan, 2019)
- Crime prevention policies (Cubbage and Smith, 2009)
  - Better lighting, patrolling, and surveillance (Haans and de Kort, 2012)
  - Empowerment of women (Chibber et al., 2012), collaborative engagement between activists and governments (Cole and Phillips, 2008)
- Indian context- CAW and general crime- cyber, property,hate, caste based (Mukherjee et al., 2001; Kabiraj 2022; Kshetri, 2016; Prasad, 2013; Sharma, 2015; Basu 2021)

This paper

- Causal factors- consistently predict crime against women and general crime in India
- Spatial correlation in crime across districts using longitudinal analysis
- Count data-crime
- Different estimation methods- consistent predictions of covariates impacting different crimes

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Theoretical approaches

- Transformative theory
- Empowerment
- Climate related

Variables and Data Sources

NCRB

(Crime in India)

(per lakh population)

- **Women** -cruelty, dowry, molestation, kidnap of women, rape
- **Body**- murder, culpable homicide, kidnap total, attempt to murder
- **Property**-burglary, robbery, theft
- **Public order** -riots

Census of India

National Oceanic and Atmospheric Administration

Indian Meteorological Department

- **Economic-** Nightlight (proxy for economic growth)
- **Social-** female workforce participation rate (FWP), female-male ratio (FMR)-literacy rate (lit)
- **Climatic**-rainfall and temperature

640 geographical districts -all states and UTs from 1991 to 2011

Data Description

- Crime rate-thirteen types of crime
  - CAW-Rape, Kidnapping and abduction of women and girls,Dowry Death, Molestation,Cruelty by husband and relatives
  - General-against body-Murder, Attempt to commit murder, Culpable homicide not amounting to Murder,Kidnapping and abduction
  - Property-Theft, Burglary, Robbery
  - Public Order-Riots
- Covariates- social, economic and climatic
  - Nighlight (NTL) and NTLsquare proxy to economic growth
  - Nightlight deviation within districts (measured by dispersion, SD)- measure of inequality-NTLsd
  - Climatic variables- a) rainfall-positive influence on agricultural growth, b) higher temperatures-conflict and agrarian stress

Empirical Model

- Spatial dependence among variables
- Count data-Panel Poisson model with fixed effects
- District level longitudinal data
- verify robustness of the result using different software

Empirical Model

- Fixed effects panel model

$$Y_{it} = \alpha_{it} + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \beta_8 X_{8it} + \mu_i + \eta_t + u_{it}$$

  - Y = Crime rate (by type of crime), X = Social, economic and climatic
  - μ = State specific effects
  - η = District specific effects

Empirical Model

- Spatial Regression-test for spatial interaction effects
- Row normalised contiguity matrix
- Spatial Autoregressive Model (SAR)

$$Y_{it} = \alpha_{it} + \beta_1 X_{it} + \rho W Y_{it} + \mu_i + \eta_t + e_{it}$$

  - Y = Crime rate, X = Vector of all X variables, W= Spatial Weight Matrix,
  - ρ = Spatial autoregressive coefficient (estimate of interaction effect among dependent variables)

Empirical Model

- Poisson panel model with fixed effects
- crime data-treated as count data
- number of events is modeled as a Poisson random variable with a probability of occurrence being

$$Prob(Y = y|x) = \frac{e^{-\lambda}\lambda^{y}}{y!}$$

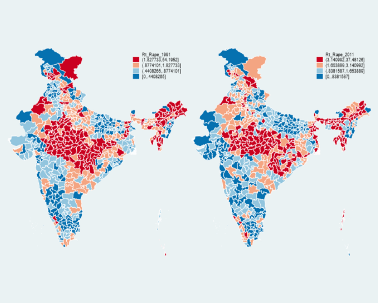
  - y=count for one group or class, λ= mean count over all groups, e= base of the natural logarithm
  - random variable Y is said to have a Poisson distribution with a mean (and variance) λ
  - Poisson distribution is specified with a single parameter λ
  - incidence rate λ is determined by a set of regressor variables

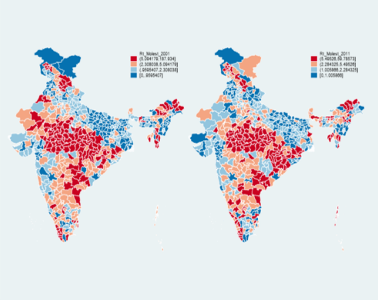
$$ln\lambda = \beta_{it} + \beta_1 X_{1it}$$

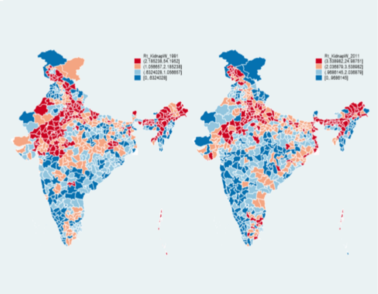
Summary Statistics

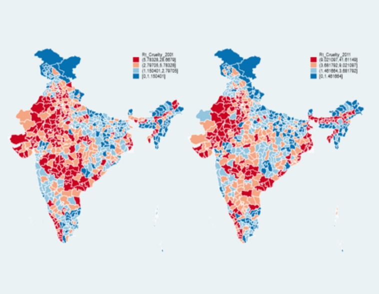
Variables	Observati	Mean	Std. Dev.	Min	Max
Dependent Variables					
Crime Against Women					
Cruelty by Husband & Relatives	1923	3.385757	5.177747	0	41.61149
Dowry deaths	1923	0.434671	1.003325	0	24.05695
Molestation	1923	2.745114	6.921004	0	187.934
Rape	1923	2.153012	2.92293	0	54.1952
Kidnapping and Abduction	1923	1.982973	2.583781	0	54.1952
Crime Against Body					
Murder	1923	4.027577	5.756268	0	137.9514
Attempt to Commit Murder	1923	3.267121	6.05348	0	136.9688
Culpable homicide not Amounting to Murder	1923	0.369417	0.901068	0	23.91429
Kidnapping & Abduction - Total	1923	2.888066	3.608111	0	64.04887
Crime against property					
Robbery	1923	2.268358	3.468428	0	73.90255
Burglary	1923	12.99271	36.85067	0	1241.563
Theft	1923	39.40537	307.3517	0	11139.58
Crime against public order					
Riots	1923	9.382189	44.54233	0	1468.197
Independent Variables					
Temperature	1923	15.6443	4.969346	0	29.00238
Rainfall	1923	1236.09	619.9465	185.2685	5457.906
Night time light (NTL)_median	1923	4.113625	9.700669	0	63
NTL_median square	1923	110.9759	567.6548	0	3969
NTL_Standard deviation	1923	4.968308	3.650572	0	24.14581
Female workforce participation rate	1923	25.12504	12.72715	0	64.03912
Female Male ratio	1923	933.4917	71.27609	0	1205.197
Total_literacy	1923	62.05751	15.96111	0	97.9115

Crime against women

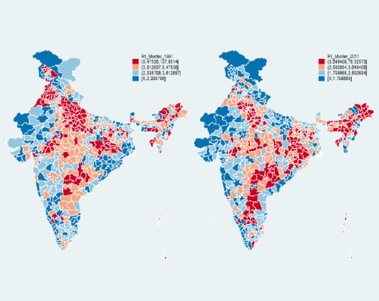


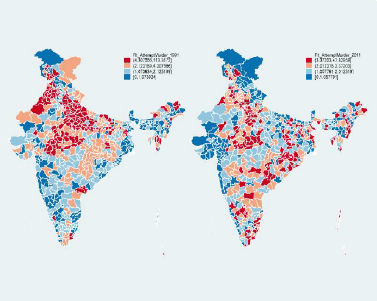


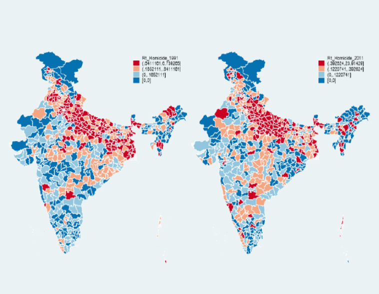


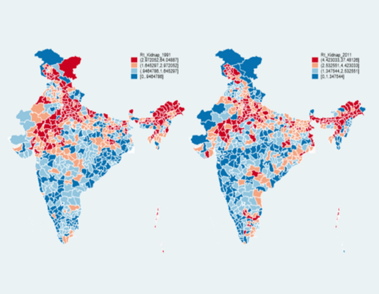


Crimes against Body

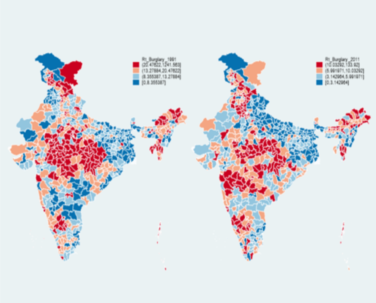


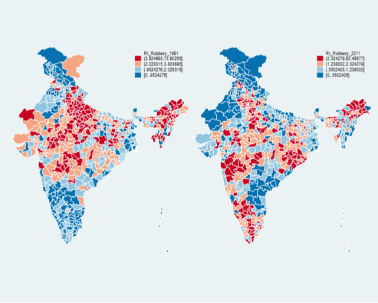


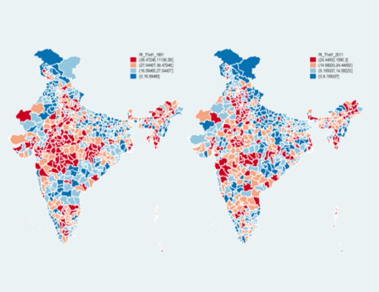


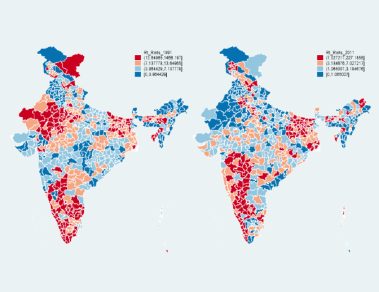


Crimes against property and public order









Panel Fixed effects (reghdfe)

Dependent variables → Independent Variables ↓	Cruelty	Dowry	Molest	Kidnap_W	Rape	Attempt to Murder	Burglary	Homicide	Kidnap_Total	Murder	Riots	Robbery	Theft
NTL Median	0.62***	-0.0532**	0.0253	0.0493	-0.0348	-0.0500	-1.94***	0.081***	0.045	-0.141*	-2.95***	0.0320	-21.21***
	(7.94)	(-2.75)	(0.60)	(0.41)	(-0.97)	(-0.65)	(-3.42)	(4.91)	(0.90)	(-2.37)	(-4.77)	(0.57)	(-3.99)
NTL Median_sq	-0.0089***	0.00056	-0.000372	-0.00279	-0.000069	-0.0035*	-0.00399	-0.0004	-0.00041	-0.00098	-0.00446	-0.00157	0.0574
	(-5.74)	(1.50)	(-0.45)	(-1.17)	(-0.10)	(-2.32)	(-0.36)	(-1.24)	(-0.41)	(-0.85)	(-0.37)	(-1.42)	(0.55)
NTL_stdev	-0.471***	0.0435*	-0.238***	-0.126	-0.154**	-0.428***	-2.51**	-0.021	-0.41***	-0.402***	-2.413**	-0.176*	-16.40*
	(-4.40)	(1.67)	(-4.16)	(-0.76)	(-3.17)	(-4.12)	(-3.27)	(-0.92)	(-5.97)	(-4.98)	(-2.89)	(-2.31)	(-2.28)
rain_averageannual	-0.00054*	0.00014*	-0.000421*	-0.000777	-0.00055***	-0.0009**	0.00077	0.00004	-0.0006**	-0.0009***	-0.00006	0.00009	0.0078
	(-1.65)	(1.68)	(-2.39)	(-1.53)	(-3.66)	(-2.82)	(0.33)	(0.55)	(-2.79)	(-3.43)	(-0.02)	(0.38)	(0.35)
tdiffmax_min_average	-0.0701	0.00704	-0.0234	0.113	-0.0561	-0.200*	0.0372	-0.030*	0.006	-0.219***	0.0448	-0.126*	-0.339
	(-0.84)	(0.35)	(-0.52)	(0.88)	(-1.48)	(-2.48)	(0.06)	(-1.74)	(0.13)	(-3.48)	(0.07)	(-2.13)	(-0.06)
fwp	0.0848***	-0.0015	-0.0257*	-0.00461	0.0187*	0.00964	0.152	-0.008*	-0.04***	0.035*	0.0875	-0.0218	2.123
	(4.48)	(-0.34)	(-2.53)	(-0.16)	(2.17)	(0.53)	(1.12)	(-2.11)	(-3.39)	(2.44)	(0.59)	(-1.62)	(1.67)
totlit	0.0339	0.0173**	0.0422**	0.0118	0.0335**	-0.0111	0.456**	-0.0076	0.033*	-0.0225	0.324*	-0.0170	4.537**
	(1.39)	(2.91)	(3.23)	(0.31)	(3.02)	(-0.47)	(2.60)	(-1.49)	(2.13)	(-1.23)	(1.70)	(-0.98)	(2.77)
fmr	-0.0020	0.00147	0.00205	-0.00714	0.000051	-0.025***	-0.124**	0.0017	0.0023	-0.018***	-0.139**	-0.0112**	-0.826*
	(-0.37)	(1.09)	(0.69)	(-0.84)	(0.02)	(-4.59)	(-3.12)	(1.50)	(0.63)	(-4.32)	(-3.21)	(-3.00)	(-2.22)
Constant	3.571	-2.313	0.277	8.719	1.859	33.67***	116.0**	-0.329	2.276	28.53***	140.5**	17.68***	634.1
	(0.61)	(-1.63)	(0.09)	(0.98)	(0.70)	(5.98)	(2.78)	(-0.27)	(0.61)	(6.52)	(3.10)	(4.28)	(1.63)
Observations	1923	1923	1923	1923	1923	1923	1923	1923	1923	1923	1923	1923	1923
Loglikelihood of fixed-effects-only regression	-4914.3	-2154.8	-3678.0	-5680.1	-3369.5	-4833.3	-8694.4	-1876.4	-4053.6	-4372.7	-8872.1	-4210.6	-12988.1

SAR Model with District fixed effects (Stata xsmle)

Dependent variables → Independent Variables ↓	Cruelty	Dowry	Molest	Kidnap_W	Rape	Attempt to Murder	Burglary	Homicide	Kidnap_Total	Murder	Riots	Robbery	Theft
NTL Median	0.421***	-0.0352	0.0231	0.143	-0.0301	-0.0463	-2.222	0.0822*	0.0460	-0.113	-2.986	0.00327	-22.93
	(6.24)	(-0.99)	(0.32)	(1.20)	(-0.40)	(-0.28)	(-1.11)	(2.03)	(0.53)	(-0.80)	(-1.29)	(0.03)	(-1.37)
NTL Median_sq	-0.00591***	0.000461	-0.000923	-0.00209	-0.000210	-0.00298	-0.00497	-0.000409	-0.00114	-0.00109	-0.00512	-0.00141	0.0493
	(-4.63)	(0.80)	(-1.20)	(-0.84)	(-0.32)	(-1.54)	(-0.37)	(-1.26)	(-1.10)	(-0.90)	(-0.33)	(-1.18)	(0.46)
NTL_stdev	-0.294**	0.0438	-0.224*	-0.0350	-0.152	-0.369**	-2.750	-0.0195	-0.326**	-0.364*	-2.470	-0.176	-18.16
	(-2.81)	(1.34)	(-2.54)	(-0.19)	(-1.82)	(-3.07)	(-1.34)	(-0.52)	(-3.10)	(-2.50)	(-1.10)	(-1.38)	(-0.97)
rain_averageannual	-0.000339	0.0000810	-0.000165	-0.000914*	-0.000460	-0.000721*	0.00149	0.0000379	-0.000236	-0.000516	0.000166	0.00000810	0.0126
	(-1.23)	(1.43)	(-0.76)	(-2.21)	(-1.32)	(-2.42)	(1.07)	(0.66)	(-0.82)	(-1.67)	(0.11)	(0.02)	(1.14)
tdiffmax_min_average	0.0550*	-0.0210*	0.0633***	-0.0938***	0.0251	-0.0180	0.0889	-0.00163	0.0606**	0.0178	0.139	0.0248	1.728
	(2.22)	(-2.40)	(4.28)	(-3.65)	(1.56)	(-0.81)	(0.60)	(-0.31)	(3.24)	(0.90)	(0.91)	(1.12)	(1.45)
fwp	0.0577***	0.00364	-0.0157	0.0481***	0.0132	0.0187	0.0466	-0.00940*	-0.0182	0.0320	0.0639	-0.0241	1.328
	(3.34)	(0.48)	(-1.29)	(3.49)	(1.22)	(0.91)	(0.21)	(-2.27)	(-1.30)	(1.66)	(0.26)	(-1.69)	(0.71)
totlit	0.0510***	0.0246***	0.0241*	0.122***	0.0316**	0.0295	0.160	-0.00734	0.0325*	-0.00328	0.252	-0.00452	2.460
	(4.04)	(5.00)	(2.08)	(7.41)	(2.68)	(1.32)	(0.64)	(-1.47)	(2.31)	(-0.17)	(0.87)	(-0.29)	(1.13)
fmr	-0.00189	0.00159	-0.000335	-0.0000112	0.000337	-0.0192	-0.144	0.00202	0.000632	-0.0138	-0.142	-0.0106	-0.964
	(-0.52)	(0.77)	(-0.08)	(-0.00)	(0.08)	(-1.76)	(-1.46)	(0.98)	(0.12)	(-1.61)	(-1.24)	(-1.78)	(-1.27)
rho	0.609***	0.216***	0.512***	0.302***	0.174*	0.339***	0.0519	0.0582	0.565***	0.460***	0.0498	0.345***	-0.00919
	(18.58)	(4.21)	(9.71)	(4.00)	(2.38)	(5.80)	(1.37)	(1.69)	(10.40)	(6.63)	(1.02)	(6.27)	(-0.67)
Observations	1923	1923	1923	1923	1923	1923	1923	1923	1923	1923	1923	1923	1923
R-squared	0.452	0.139	0.126	0.132	0.0813	0.0501	0.0937	0.0509	0.122	0.118	0.0947	0.0635	0.0569
Log-likelihood	-4579.9	-2125.5	-3512	-5672.8	-3324.3	-4746.2	-8641.8	-1830	-3815	-4205.3	-8797.7	-4147.6	-12938.7

Poisson regression models with multiple high-dimensional fixed effects (ppmlhdfe)

Dependent variables Independent Variables	Cruelty	Dowry	Molest	Kidnap_W	Rape	Attempt to Murder	Burglary	Homicide	Kidnap_Total	Murder	Riots	Robbery	Theft
NTL_median	1.025	0.918	1.039**	0.986	1.027	1.1***	1.045819	1.18***	1.05***	1.092316	0.984029	1.063324	0.946201
	(-1.46)	(-0.94)	(-1.92)	(-0.43)	(-1.14)	2.85	0.74	6.34	2.63	3.1	0.17	2.4	0.43
NTL_median_sq	0.99***	1	0.999***	1	0.999	0.99***	0.999295	0.99***	0.99***	0.99***	0.999904	0.99**	1.000693
	(-2.67)	(-0.03)	(-2.44)	(-0.08)	(-1.54)	3.48	0.85	6.74	2.96	3.44	0.07	2.2	0.4
NTL_stdev	0.991	1.069	0.951***	1.029	0.933***	0.933047	0.93***	0.944122	0.94***	0.93***	1.003596	0.94***	0.966475
	(-0.43)	(-1.38)	(-2.51)	(-0.55)	(-3.57)	1.56	2.2	1.39	3.44	2.45	0.08	2.71	0.79
rain_averageannual	0.999***	0.999***	1	1***	1	0.999708	0.999823	1.000184	0.999986	0.999891	0.999148	1.000089	0.998931
	(-3.76)	(-2.07)	(-0.39)	(-2.71)	(-0.26)	2.26	0.65	1.53	0.18	1.15	1.63	0.75	1.27
tdiffmax_min_average	0.958***	1.034	0.934***	0.959	0.9436***	0.934728	0.93258	0.914846	0.943178	0.914388	0.812207	0.914937	0.826959
	(-2.37)	(-0.55)	(-3.27)	(-1.49)	(-3.27)	1.98	1.17	2.65	3.27	3.85	1.89	3.59	1.28
FWP	0.994	0.944***	0.9782***	0.97	0.993*	0.969573	0.97609	0.955902	0.975993	0.977262	0.944122	0.978534	0.94535
	(-0.76)	(-3.16)	(-5.36)	(-1.55)	(-1.81)	3.71	3.34	5.81	6.19	4.62	4.11	4.78	3.64
TotLit	1.02***	1.045***	1.011	1.025***	1.016*	1.012882	1.038212	0.986393	1.009303	1.007579	1.045923	1.005666	1.090788
	(-3.7)	(-2.14)	(-1.37)	(-2.87)	(-1.89)	1.34	2.33	1.61	1.25	0.87	1.72	0.68	2.18
FMR	1.003***	1.015***	1.001	1.011***	1.002***	1.003496	1.003456	1.001141	1.000749	1.002383	1.010555	1.000649	1.009323
	(-2.33)	(-2.19)	(-1.2)	(-4.27)	(-2.05)	2.61	2.66	1.19	1.07	2.77	5.28	0.83	2.93
Constant	0.380602	0.0000003**	3.553738	0.00023***	0.563268	0.653116	0.500574	3.247872	6.258872	2.723724	0.007852	7.389056	0.009159
	(-0.72)	(-2.01)	(-1.18)	(-4.86)	(-0.48)	0.37	0.54	1.24	2.19	1.14	3.5	2.08	2.14
Observations	1804	1631	1862	1870	1884	1889	1899	1722	1884	1896	1828	1870	1899
Psuedo R-square	0.65	0.355	0.314	0.625	0.294	0.323	0.498	0.261	0.319	0.271	0.571	0.296	0.653
Loglikelihood of fixed-effects-only regression	-7335.3	-1593.1	-4281.7	-7211.1	-3880.1	-6054.4	-20744.3	-1449.4	-4939.5	-5735.7	-24288.1	-4492.7	-131003

SAR Results

ρ positive and significant		
Variables	significant and positive	significant and negative
NTL	cruelty,C.homicide,kidnapW	burglary,riots,theft
NTLsq		cruelty, molest, A.murder, C.homicide, robbery, kidnapT
NTLsd	dowry	cruelty, molest, A.murder,rape, burglary, murder, riots, robbery, kidnapT
Rainfall	dowry,burglary,theft	cruelty,A.murder,rape,kidnapT
Temp	cruelty, molest, kidnapT,robbery, theft	dowry, kidnapW
Literacy	cruelty,dowry,molest,rape, kidnapW, KidnapT, theft	C.homicide
FMR		murder,riots,theft,robbery, A.murder, burglary
FWP	cruelty,kidnap,murder,rape	molest,C.homicide,kidnapT,robbery

Poisson Panel Fixed effects Results

Poisson regression model		
Variables	significant and positive	significant and negative
NTL	cruelty, molest, rape, A Murder, CH, KidnapT,robbery	burglary,riots,theft
NTLsq		cruelty,rape,molest, AMurder, C Homicide, robbery, murder, KT
NTLsd	dowry	molest,rape, A Murder, burglary, CH, murder,robbery, KT
Rainfall	KW,CH	cruelty,dowry,AM,riots,theft
Temp		cruelty,molest,rape,AM,burglary,CH
Literacy	cruelty,dowry, Mol,rape,KW, KT,AM,burg, riots, theft	CH
FMR	cruelty,dowry,molest, rape, KW, KT, AM, burg,riots, murder,riots,theft	
FWP		dowry,mol,rape,KW,KT,AM,burgla riots, CH, theft, riots,robbery

Results

Unanimous spatial regressions results (software)		
Variables	significant and positive	significant and negative
FWP	cruelty	attempt murder, burglary, C.homicide, kidnapT, riots, robbery, theft
Rainfall	robbery	cruelty, molest, attempt murder, C.homicide, riots
NTL	cruelty	theft
NTLsd	dowry	attempt murder, burglary, kidnapT, murder, riots
NTLsq	dowry, theft	Cruelty,attempt murder, riots
Literacy	cruelty, dowry, molest, rape, kidnap	C homicide, murder, riots, robbery
Temperature	rape, kidnapT	murder, riots
FMR	cruelty, molestation	theft

To conclude

- Certain factors consistently predict crime
  - rainfall rise-reduces two CAW(cruelty, molest), three non CAW-riots, CH and Attempt murder (Sekhri and Storeygard, 2014; Blakeslee et al., 2021)
  - rise in inequality reduces five non CAW, increases one CAW (contrast to received literature)
  - Literacy-reduces four non CAW (rule abiding nature, better civic sense), increases four CAW(empowerment and backlash effect)
  - FWP reduces (seven) non CAW-(human capital investment, reduced wage gap), increases CAW (backlash, IPV)
- Whether predictors of CAW also predict non CAW?
  - contrasting results-many variables-NTL (negative CAW, positive-non CAW), Inequality(positive CAW, negative-non CAW)
  - FWP, Literacy, FMR - positive effect- CAW, negative-non CAW
- Compatibility of results from different methods

Thank You