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DETERMINANTS OF CRIME ACROSS CONFLICT AND NON-CONFLICT STATES IN INDIA

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The paper has two main goals. First, using district level panel data we examine the key determinants of violent crime, non-violent crimes and crime against women in India for the period 1990-2007. Second, using the district level variation in Maoist conflict, we examine how conflict affects both crime as well as the roles of various determinants of crime. In addition to looking at the conventional determinants of crime (law enforcement and economic variables), we examine how variation in sex ratios affects crime. We also look at whether the gender of the chief political decision maker in each state (i.e. the Chief Minister) affects crime. We find that improvements in arrest rate decrease the incidence of all types of crimes. Socio-economic variables have relatively little explanatory power. We also find evidence that unbalanced sex ratios, in particular in rural areas, may adversely affect crime. Female political representation with greater decision-making power particularly diminishes violent crime and crime against women. Finally, we find a counter-intuitive result that in districts affected by the Maoist insurgency, all types of crime are lower and we offer explanations for why that may be the case.
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INTRODUCTION

Crime and conflict has been at the heart of policy debates across many countries and in this paper we try to analyse the relationship between crime and conflict in India by analysing a particular conflict viz. the resurgence of Maoist (or Naxalite) conflict [1]. We do this by looking at what factors impact crime across districts affected by Maoist conflict vs. districts not affected by it. While the analysis of crime across developing countries sometimes seem to take a backseat in the face of other issues such as poverty and lack of effective governance, it is increasingly understood that there is an intimate relationship between crime, conflict and socio-economic backwardness [2], [3],[4], [5]. This paper looks at the crime patterns that emerged in India for the period 1990-2007 and analyses how the changing socio-economic and demographic factors affected crime. India in spite of its economic advancement has been facing various instances of conflict and the post 2004 revival of Maoist conflict presents a particular challenge both in terms of the burden on law enforcement in keeping it under control as well as the longer term effect of changing economic conditions that may have precipitated the conflict in the first place.

There could be several reasons for why the roles of factors affecting crime such as law enforcement may vary across conflict and non-conflict districts. There may be differences in the distribution of preferences (e.g. attitudes to risk, tolerance for violence) of the population across two areas (i.e. conflict and non-conflict areas) which could fuel both conflict related violence as well as affect other types of criminal behaviour. Socio-economic factors are often the cause of conflict but without disentangling the cause-effect issue here one can still see differences in impact of some factors on crime across conflict and non-conflict states. Distribution of people from different castes may matter across all states (and there is certainly evidence that this may play an important role in violent crime in India, [3, 6]) but its role may be particularly strong in so-called 'conflict' states. Advances in literacy may lower crime across all states but it may have particularly strong impact in conflict ridden areas.

We begin by looking at the broad patterns of crime across various types for districts in the 16 major states of India and estimate the different determinants of crime. In the second part of the paper, the districts are categorised as red-corridor (those where the Maoist conflict is mostly prevalent) and non-red corridor states and we look at whether there are any differences in the marginal effects of our determinants across conflict and non-conflict states. The literature on determinants of crime in India has addressed some of the issues raised in this paper [6] [7]. However, in [6] the authors do not differentiate between the different crimes categories and are therefore unable to capture the heterogeneity in crime rates within states. This paper addresses these issues and establishes a relationship as posited in the classical deterrence hypothesis [8]. Further, in [7] the authors explore a related question to the one posited in the second part of this paper but do not explore any mechanism that explain why conflict may impinge on crime and also fail to establish a significant relationship.

Our choice of determinants is based on what we believe to be important factors that affect costs and benefits of committing crime and thus is in the spirit of the literature that finds empirical proxies for the model in [8]. While we follow the literature in this area to select the determinants we consider two additional factors which can potentially affect crime, especially in India. The first is the sex ratio. Unlike most developed countries which have a stable, 'naturally balanced' sex ratio, there is considerable variation and imbalanced in sex ratios across Indian states [9]. Second, we believe that female decision making in the political process may affect crime particularly violence and crime against women as female leaders may make fighting such crimes a priority. We now provide some background of the Maoist insurgency to motivate our analysis of conflict vs. non-conflict states.

CONFLICTS IN INDIA AT THE MICRO LEVEL

India has been home to several conflicts at the sub-national level (the so called 'micro conflicts'). The major conflicts in India are the Maoist/Naxalite[1] extremist movement, the Hindu-Muslim communal conflict, the separatist movements in the north eastern states and Islamic fundamentalist terrorism There are some other conflicts and insurgencies such as the Tamil insurgency movements but the above mentioned are the major conflicts as accounted by intensity of conflict [10]. These major conflicts are spread out across the country and vary substantially in their magnitude of incidence.

In this paper we focus on the Maoist conflict which is the longest micro-conflict in India. It is considered the major conflict in India and its control/ cessation is high on the political agenda of the Central Government [2]. Of the main motives behind the start and diffusion of the conflict are unequal land distribution, land rights etc., which mostly affect lower castes and ethnic tribal groups [1], [10], [11]. The land-related conflict started in 1967 in the *Naxalbari* village in West Bengal and spread out mostly due to underdevelopment and the support it gained from political parties as the Communist Party of India (Marxist). From the first years of the Naxalite insurgency until 2000 the conflict was marked by a fragmented movement with numerous ideological opposing Naxalite groups, see [1] for an overview. It wasn't until 2004 that the two major groups within the Naxalite movement merged forming the Communist Party of India -Maoist. This was the starting point of the neo-Naxalite conflict and this is what we will use as the time period when conflict starts. The intensity of the conflict is highly heterogeneous both across districts within affected states as well as across states [12].

The literature on the relation between conflict and economic growth suggests that civil conflict negatively affects economic growth [13, 14]. This relation has also been shown to hold true for the Naxalite affected districts, which are among the poorest in India [12]. One of the major causes pointed out in the literature for the uprising and continuing of the Naxalite conflict are institutional and colonial legacies that caused underdevelopment in these regions [10]. One other strand of the literature on conflict establishes that adverse climate shocks (or adverse natural resource shocks) increase the intensity of conflict. The mechanism

[1] Maoist and Naxalite are used interchangeably throughout the paper as both these terms refer to the conflict.
[2] In 2006, the Indian Prime Minister stated publicly that the Maoist conflict was "the single biggest internal security challenge ever faced by our country" in Economist, 25 Feb 2010, *Ending the Red Terror*.

underlining this relation is that adverse climate shocks are correlated with income shocks which provide an intensification of conflicts as a means to fight over resources and alleviate the income constraints [15]. Others point out that the there is a strategic element to the relation i.e. areas with adverse climate shocks are strategically chosen by Maoist insurgents as target areas for conflict. [12].

Our analysis abstracts from the causes of the Maoist conflict but instead asks what role this has had (e.g. through the policies implemented to control insurgency) on various types of crime. This is important because conflict states may experience higher crime particularly violent crime because of the insurgency and second by lowering economic growth conflicts may reduce the opportunity cost of committing non-violent crime as well. Further, a general breakdown of law and order may reduce the deterrence effect of law enforcement. Acting against this, there may be an informal law enforcement role that the insurgents may take on leading to a lowering of crime in general. Finally, the conflict has led to an increased military presence in affected states which may have the unintended consequence of lowering rates of other types of crime.

Similarly [16], address the positive consequence for growth of counterinsurgency policies, our paper points to a related conclusion. Our estimates suggest that in conflict areas crime decreased due to the improved policing.

EMPIRICAL STRATEGY AND DATA

Our empirical specification to analyse major determinants of crime in India is given by the following equation:

$$C_{d,s,t=}\beta_0 + X_1\beta_{d,t} + X_2\beta_{s,t} + \delta_d + \gamma_s + \mu_t + \varepsilon_{d,s,t} \qquad (1)$$

where $C_{d,s,t}$ is the log of crime rate per 100,000 population in district *d* of state *s* at time *t*. X_1 is a vector of district-specific socio-economic explanatory variables and X_2 is a vector of state-specific variables. The error-term is given by $\varepsilon_{d,s,t}$. Crime and violence rates may depend on unobservable factors that are persistent throughout time such as social norms, tolerance of crime etc. which can vary across districts. As a result, we include district fixed-effects to account for time-invariant characteristics. Similarly, we also include state specific fixed effects to account for factors that are heterogeneous across the Indian states. Finally, we also include time-fixed effects to account for national time-variant effects on crime. In all regressions we use robust standard errors clustered at the district-level to address problems of serial correlation and allow for heteroskedasticity.

Indian states have independent decision making power over law and order policy. As such, different states may allocate different resources to policing and security. We allow for this by including several state-specific variables that control for deterrence. We include crime-specific arrest rates and strength of the police force (per 100,000 population). We expect that an increase in deterrence decrease crime. However, allocation of police resources may not be homogenous within-states. District-specific characteristics and special interests such as electoral goals, location of firms etc., may lead to heterogeneous allocation of security goods. However, information on district-level deterrence measures is not available and thus, we include these measures varying only at the state-level. Unobservable time-varying and time-invariant factors that could influence the allocation of resources would be captured by the inclusion of $(\delta_d + \gamma_s + \mu_t)$.

We collected district-level data from 16 different crime categories from the National Crime Records Bureau (NCRB). Using these we grouped crime into 4 major groups as defined by the Indian Penal Code. We separately considered violence, property, economic crimes and crimes committed against women. We ended up with a panel of 346 districts between the years 1990- 2007, across 16 major states of India. In addition, we use state-level data on police strength (civil and armed) and arrest rates per category[3] to obtain measures of law enforcement. This information is available only at the state-level and not at the district-level. Socio-demographic data at the district-level is available decennially from the Census 1991 and 2001. We match district boundaries to those of 1991 and match state boundaries to those of 2000. Finally, we match this information with political variables collected from election reports from the Electoral Commission. We also include real GDP data taken from the Reserve Bank of India, measured at the state level. Descriptions of all variables are presented in Table 1.

The Government of India (GOI)'s Reimbursement of Security Related Expenditures (SRE) Scheme identifies the districts that have been affected for the last 5 years by the Naxalite conflict (evaluated by the intensity of the conflict) [17], [11]. The central government released Rs. 5 billion (approx. $16 million) to affected states governments reimbursing them

[3] Arrest rates were not available for molestation, sexual harassment, cruelty by husband and relatives and kidnapping and abduction of females thus, to compute arrest rates of crimes against women we use only rape and dowry deaths.

for expenditures incurred as of the financial year 2004-05. These expenditures included reimbursement for expenditures "relation to insurance, training and operational needs of the security forces, rehabilitation of Left Wing Extremist cadres who surrender in accordance with the surrender and rehabilitation policy of the State Government concerned, community policing, security related infrastructure for village defence committees and publicity material" (Naxalite Management Division, Ministry of Home Affairs, GOI).

We use this information available from the SRE to construct our Red Corridor area dummy. Among the states in our sample, 7 have districts affected by the Naxalite conflict[4]. We use the report produced by the Ministry of Home Affairs [17] to construct a dummy variable for districts affected by the Naxalite insurgency post-revival. This gives us a total of 46 districts which are considered conflict affected areas, as per the 1990 boundaries. This measure is imperfect as it does not capture the intensity of the conflict or the expansion of the Maoist insurgency since its inception. It however gives a useful summary measure of conflict.

We employ the following specification to estimate the marginal impact of being in a conflict state:

$$C_{d,s,t=}\beta_0 + X_1\beta_{d,t} + X_1\beta_{d,t} \times RC_{d,t} + X_2\beta_{s,t} + X_2\beta_{s,t} \times RC_{d,t} + \beta_k RC_{d,t} + \delta_d + \gamma_s + \mu_t + \varepsilon_{d,s,t} \qquad (2)$$

where we have augmented specification (1) by including the term $RC_{d,t}$ and the interaction terms with both state and district-level explanatory variables. All variables are as defined in (1) and $RC_{d,t}$ is a dummy variable for districts affected by Naxalite conflict post 2004. This specification explicitly tests for the differential effects of conflict on factors determining crime. Results are presented in Table 4 and 5. A concern in all these specifications is the potential multicolinearity of variables but we do variance inflation checks which suggest that this is not an issue.

One final concern to address is under-reporting. Police recorded crimes depend on reporting levels and as result, some crimes may be left unreported or there can be differences in reporting behaviour across states. Further, such under-reporting may not be uniform and the probability of reporting can be influenced by several factors as perceptions of policing, citizen empowerment etc. which vary across states. Further, the figures that NCRB report

[4] Considering the 1990 borders, the Naxalite conflict affected states are Andhra Pradesh, Bihar, Madhya Pradesh, Maharashtra, Orissa, Uttar Pradesh and West Bengal.

consider only the principal crime (i.e. the highest recorded offence). Thus, it is likely that our estimates are affected by under reporting bias. It may of course be that such (under) reporting rates are stable across time in which case this will not affect our estimation but this does not appear to be the case [18]. We address these concerns in two ways. First, district fixed effects control for time-invariant district specific factors and as long as such fixed district-specific factors cause persistent under-reporting of crime in a district, the inclusion of fixed effects should mitigate some of the concerns over crime misreporting. Second, in both (1) and (2) richer states may show higher crime rates due to different reporting behaviour or different incentives to commit crimes (i.e. in richer states the incentive to commit property crimes is higher; richer states are also correlated with higher education levels which could increase reporting). Therefore, we conduct a robustness test by weighting the estimation of specifications (2) using the inverse of the income level as the weight. Thus, richer states have lower weight than poorer states. Results are presented in Table 4. It is also worth noting that work comparing reported and self-reported crimes in India shows that even if crime is under-reported the use of police-reported statistics is still very informative [19].

RESULTS

In Table 2 we present the difference in means tests between Red Corridor states and non-Red Corridor states. We find that areas affected by conflict are different from non-conflict areas. Crime rates are higher in non-conflict states in comparison to conflict states. Arrest rates are higher in conflict states but, police force is lower. However note that in conflict states police force is supplemented by paramilitary forces so our measure of law enforcement in conflict states does not account for these forces for whom we do not have data[5]. Figure 1 depicts the trends in crimes across categories by All- India, Maoist and Non-Maoist states. First, it is striking to see that whilst property crimes have decreased, violence has increased post-liberalization reforms of 1991. Economic crimes have also increased though crime rates of this crime category are much lower. Property crimes have decreased faster in Maoist states then in Non-Maoist states. Similarly, violence and economic crime rates have been following the same trend as the rest of India though with lower rates.

[5] [10] mentions an extra 33 battalions of Central paramilitary forces and 32 battalions from the India Reserve Forces have been deployed to conflict affected states in order to increase personnel per capita.

In Table 3 we present the results for determinants of crime and in Table 4 we present the results of determinants of crime comparing conflict and non-conflict areas. The coefficients of arrest rates are negative and significant across all crime categories. For instance in Table 4 a 1% increase in arrest rates decreases property crime by 0.19%, violent crime by 0.32%, economic crime by 0.06% and crime against women by 0.21%. Thus, there I a deterrence effect of increased arrest rates for all crime categories. However, police force has a mixed effect. For violent crime and crime against women higher police force decreases crime rate but for non-violent crimes the impact is opposite. The latter be picking up some reverse causality though lagged values of police force give similar results. The positive coefficient of police force could also come from the fact that a higher police force may lead to more non-violent crime being recorded (a police force short on staff may not take these crimes seriously). Finally it is worth noting that police numbers are an imperfect measure of policing given that conflict states have additional paramilitary forces who co-operate with the police.

The role of female political participation is ambiguous and depends on the level of decision-making we consider. An increase in the number of seats held by women in state legislatures does not seem to have an effect on crime. However, having women as Chief Ministers decreases violent crime and crime against women. The effect is consistent across specifications and when estimating the effects across conflict status (Table 4) the role of a woman Chief Minister in reducing crime against women turns out to be stronger in conflict states. Thus, decision making power in the hands of women leads to a decrease in crime.

Increase in employment rates reduce economic crime and crime against women. This result is also consistent across specifications. Higher income per capita increases crimes for all categories. This is consistent with the fact that in India an increase in income has increased inequality which may increase crime [20]. However, it could also be the case that higher incomes (or richer states) are associated with higher reporting rates. If the positive coefficients are interpreted to mean that poorer states have less crime, then the effect turns out to be stronger in conflict states as seen from the interaction terms between income and red corridor dummy in Table 4.

The classical theory of crime suggests that criminals engage in illegal activities as an occupational choice or investment opportunity. As a result, individuals decide on whether or not to commit crime based on the expected utility of engaging in criminal activities as opposed to investing in education or legitimate work. As a result the effect of increased number of literates is expected to reduce crime. In Tables 3 and 4 we do not find evidence of this relation in the context of India.

As mentioned earlier, the role of caste is potentially important particularly for explaining violent crime. However, the percentage of SC or ST in the population does not explain crime in a consistent manner though as seen in Table 4 we find that a higher share of SC population increases economic crime and crime against women.

From Table 4 we can see that in districts affected by the conflict after the year 2004, crimes rates are lower and these results are significant across all categories. This suggests that conflict is not causing a crime/ violence diffusion effect i.e. in conflict areas, the fact that there has been a long standing conflict that increased in its intensity after 2004 is not related to an increase in other types of violence and crime. In fact, our estimates suggest that increased attempts to reduce the intensity of the conflict (e.g. through increases in police strengths) explain why crime fell in these areas.

We expect that sex ratios (females per males) have an inverse relation with crime given the propensity of males to commit crime is supposed to be higher than females [9]. In Table 3 we see that a decrease in sex ratio mainly when defined as the rural female-male ratio increased crime. In Table 4 the interaction terms between sex ratios and the red corridor dummy for violent crime and crime against women have positive coefficients implying that an increase in the number of females relative to males leads to an increase in such crimes particularly in conflict areas.

Finally we note that results from the weighted regressions presented in Table 5 are qualitatively unchanged from the results described above based on Table 4. This suggests that our main findings are robust to reducing the importance of richer states instead of treating all states as equally important in the estimation. In other words our main results are not driven by states of a particular economic size – either rich or poor.

CONCLUSION

Our analysis of crime and conflict in India shows that deterrence in the form of arrest rates matter in lowering crime but a number of socio-economic variables do not systematically influence crime. However, women leaders matter; female Chief Ministers reduce violent crime and crime against women. Further, we have also shown that social norms and practices that influenced and continue to increase the population gender gap may, in part, explain why violent crime against women continues to rise. States that are conflict ridden actually have lower crime rates. This is an intriguing finding and we hope that future work will look at whether this is due to larger expenditure on law enforcement with paramilitary forces complementing the police or whether Maoist dominance prevents other types of crime in these areas. If it is the former, then it would suggest that expenditure on law enforcement to reduce conflict may have a diffusion effect in reducing crime in general. Our results point towards this possibility but more research is needed to arrive at a firm conclusion.

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APPENDIX

FIGURE 1: CRIME CATEGORIES TRENDS IN INDIA

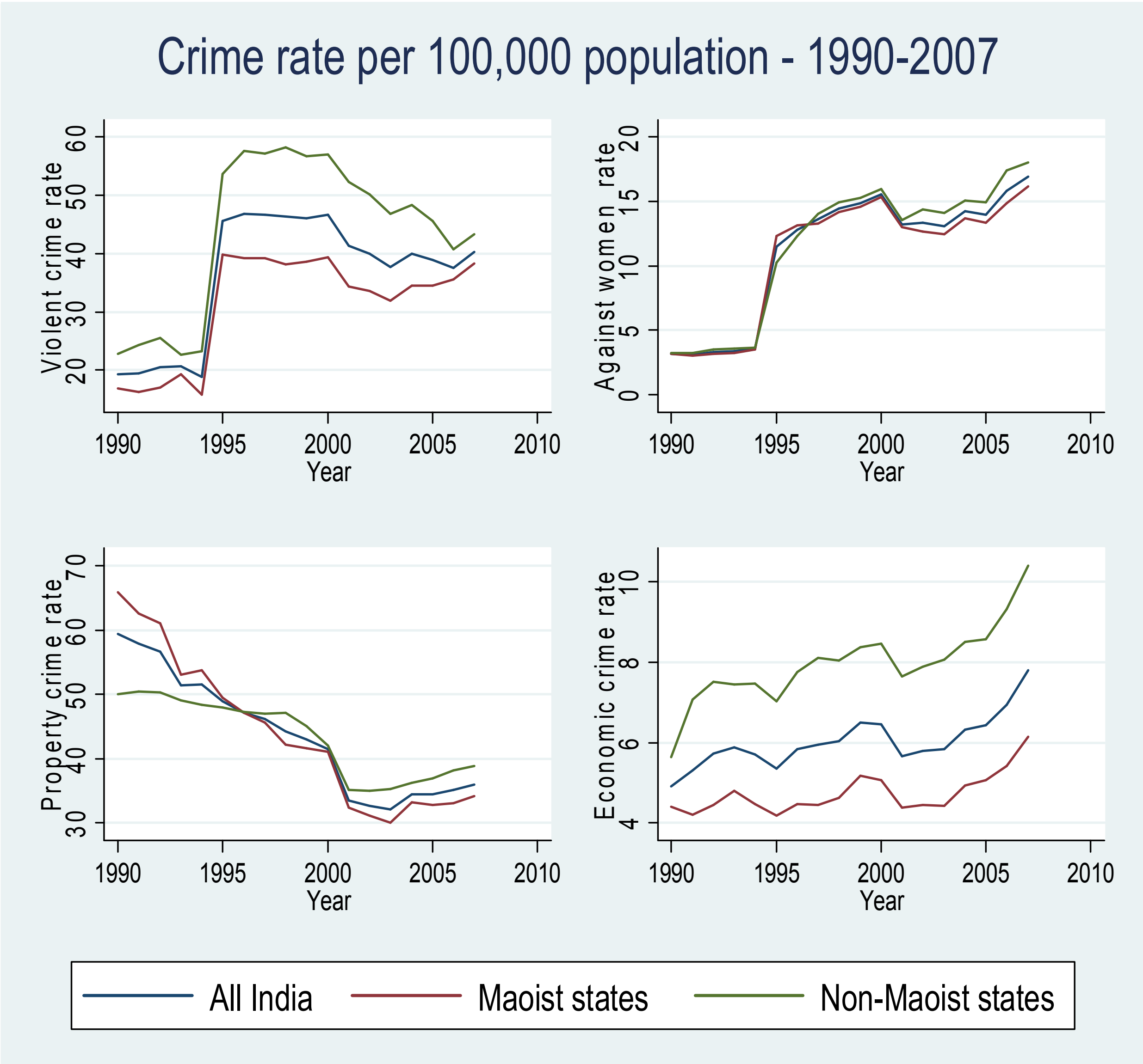

TABLE 1: DEFINITIONS OF VARIABLES

Variable	Definition	Geographical level	Source
Property crime rate	Total incidents per 100, 000 population. Includes the incidents registered under burglary, robbery, theft and dacoity.	District-level	NCRB yearly reports
Violent crime rate	Total incidents per 100, 000 population. Includes the incidents registered under total kidnappings, murder, riots, arson and hurt.	District-level	NCRB yearly reports
Economic crime rate	Total incidents per 100, 000 population. Includes the incidents registered under criminal breach of trust, cheating and counterfeiting.	District-level	NCRB yearly reports
Women crime rate	Total incidents per 100, 000 population. Includes the incidents registered under rape, dowry deaths, molestation, sexual harassment, cruelty by husband and relatives and kidnapping and abduction of females.	District-level	NCRB yearly reports
Property arrest rate	Arrests per 100, 000 population. Arrests of crimes considered under this category.	State-level	NCRB yearly reports
Violent arrest rate	Arrests per 100, 000 population. Arrests of crimes considered under this category.	State-level	NCRB yearly reports
Economic arrest rate	Arrests per 100, 000 population. Arrests of crimes considered under this category.	State-level	NCRB yearly reports
Women arrest rate	Arrests per 100, 000 population. Arrests of crimes considered under this category. Arrest rates were not available for molestation, sexual harassment, cruelty by husband and relatives and kidnapping and abduction of females thus, to compute arrest rates of crimes against women we use only rape and dowry deaths.	State-level	NCRB yearly reports
Police force	Civil and armed police force per 100, 000 population.	State-level	NCRB yearly reports
Literacy rate	Literates per total population.	District-level	Census 1991-2001
% SC/ST	Scheduled Castes/Scheduled tribes as a share of total population.	District-level	Census 1991-2001
Employment rate	Working population as a share of total population.	District-level	Census 1991-2001
Income per capita	Real GDP per capita at current prices 93-94.	State-level	Census 1991-2001
% Seats held by women	% seats held by women in State Legislature.	State-level	Election Commission reports
Gender CM	Dummy for female as Chief Minister in the state	State-level	Election Commission reports
Sex ratio	Females per Males population	District-level	Census 1991-2001
Rural sex ratio	Females per Males population- rural	District-level	Census 1991-2001
Urban sex ratio	Females per Males population- urban	District-level	Census 1991-2001
RC	Dummy variable if district is considered a part of the Red Corridor post 2004.	District-level	Ministry of Home Affairs, report

TABLE 2: DESCRIPTIVE STATISTICS

	All		Non-Maoist states		Maoist States		
Variables	Mean	SD	Mean	SD	Mean	SD	Diff
Property crime rate	41.42	34.07	42.95	34.70	31.56	27.77	11.39***
Violent crime rate	36.98	29.82	38.11	30.87	29.71	20.48	8.40***
Economic crime rate	5.55	5.85	5.84	6.15	3.70	2.69	2.13***
Women crime rate	23.58	20.61	24.20	20.34	19.59	21.88	4.61***
Property arrest rate	0.88	0.39	0.86	0.39	0.98	0.34	-0.126***
Violent arrest rate	2.36	2.67	2.34	2.78	2.49	1.72	-0.151*
Economic arrest rate	1.06	0.49	1.05	0.50	1.12	0.44	-0.072***
Women arrest rate	0.45	0.30	0.44	0.30	0.52	0.30	-0.08***
Police force	1113.39	0.63	116.83	0.69	76.17	0.93	40.66***
Literacy rate	0.43	0.18	0.44	0.18	0.37	0.17	0.071***
% ST	0.09	0.15	0.08	0.14	0.17	0.19	-0.093***
% SC	0.16	0.07	0.16	0.07	0.16	0.07	0.003
Employment rate	0.36	0.09	0.36	0.09	0.38	0.08	-0.0235***
Income per capita	9.32	0.67	9.36	0.009	9.01	0.024	0.357***
Gender CM	0.17	0.38	0.16	0.37	0.26	0.44	-0.093***
% Seats held by women	0.05	0.03	0.05	0.03	0.06	0.03	-0.005***
Sex ratio	0.77	0.25	0.78	0.26	0.75	0.19	0.028***
Rural sex ratio	1.00	0.24	1.00	0.23	1.05	0.32	-0.051***
Urban sex ratio	0.98	0.27	0.98	0.28	0.99	0.19	-0.008
RC	0.03	0.17	0.00	0.00	0.22	0.41	-0.220***

TABLE 3: DETERMINANTS OF CRIME

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Property crime rate		Violent crime rate		Economic crime rate		Women crime rate	
arrest rate	-0.205***	-0.216***	-0.322***	-0.327***	-0.0538***	-0.0539***	-0.202***	-0.199***
	(0.0445)	(0.0461)	(0.0263)	(0.0256)	(0.0197)	(0.0191)	(0.0182)	(0.0180)
Literacy rate	-0.176	0.165	0.0279	0.433***	-0.256	0.0641	-0.245	0.0794
	(0.195)	(0.124)	(0.258)	(0.164)	(0.172)	(0.205)	(0.187)	(0.121)
% SC	1.460	3.225	0.476	2.234	3.562	7.783**	2.005	5.944**
	(1.914)	(2.569)	(2.147)	(2.814)	(3.002)	(3.454)	(2.449)	(2.879)
% ST	-0.601	0.417	-1.358	0.366	-2.174	0.207	-1.487	0.819
	(0.996)	(0.955)	(1.205)	(1.401)	(1.801)	(1.572)	(1.556)	(1.146)
Police force	0.0848***	0.0732***	-0.105***	-0.125***	0.0785**	0.0643*	-0.0567	-0.0741**
	(0.0228)	(0.0217)	(0.0263)	(0.0264)	(0.0386)	(0.0383)	(0.0354)	(0.0368)
% Seats held by women	-0.298	-0.265	1.240***	1.496***	-0.193	-0.101	-0.235	-0.0793
	(0.374)	(0.357)	(0.477)	(0.468)	(0.532)	(0.540)	(0.516)	(0.507)
Gender CM	-0.00903	-0.00581	-0.192***	-0.192***	-0.0410*	-0.0409*	-0.0849***	-0.0857***
	(0.0166)	(0.0167)	(0.0240)	(0.0234)	(0.0235)	(0.0234)	(0.0239)	(0.0236)
Employment rate	0.298	0.300	-0.937*	-0.765	-1.158***	-1.003**	-1.419***	-1.178***
	(0.414)	(0.393)	(0.538)	(0.515)	(0.428)	(0.414)	(0.353)	(0.332)
Income per capita	0.729***	0.722***	0.817***	0.801***	0.358***	0.367***	1.150***	1.170***
	(0.101)	(0.0976)	(0.128)	(0.122)	(0.127)	(0.123)	(0.114)	(0.109)
Sex ratio	-0.201**		-0.00234		-0.0461		0.0212	
	(0.0859)		(0.0473)		(0.122)		(0.0795)	
Urban sex ratio		0.0297		0.0549		0.0742		0.0483
		(0.0640)		(0.0750)		(0.101)		(0.0659)

Rural sex ratio		-0.460***		-0.599***		-0.464***		-0.459***
		(0.125)		(0.114)		(0.170)		(0.132)
Observations	6,211	6,149	6,211	6,149	6,187	6,128	6,204	6,145
Adj.R-squared	0.790	0.793	0.700	0.708	0.671	0.670	0.828	0.833
All regressions include district, year and state fixed-effects. Robust standard errors in parentheses clustered at the district-level								
***** p<0.01, ** p<0.05, * p<0.1**								

TABLE 4: CRIME AND CONFLICT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Property crime rate		Violent crime rate		Economic crime rate		Women crime rate	
arrest rate	-0.188***	-0.199***	-	-	-	-	-0.210***	-0.208***
	(0.0446)	(0.0457)	(0.0266)	(0.0258)	(0.0198)	(0.0189)	(0.0185)	(0.0182)
RC* arrest rate	0.0393	-0.00134	-0.0367	-0.0439	-0.0422	-0.0491*	0.789***	0.895***
	(0.227)	(0.222)	(0.0449)	(0.0461)	(0.0281)	(0.0294)	(0.105)	(0.119)
Literacy rate	-0.0713	0.164	0.136	0.401**	-0.206	0.0120	-0.123	0.0887
	(0.140)	(0.129)	(0.225)	(0.167)	(0.167)	(0.207)	(0.132)	(0.122)
% SC	0.985	2.878	-0.150	1.906	2.985	7.367**	1.360	5.555**
	(1.826)	(2.524)	(2.108)	(2.823)	(2.829)	(3.291)	(2.293)	(2.777)
% ST	-0.415	0.430	-1.141	0.256	-2.047	0.168	-1.280	0.624
	(0.889)	(0.913)	(1.169)	(1.425)	(1.724)	(1.524)	(1.464)	(1.104)
Police force	0.0862***	0.0772***	-	-	0.0689*	0.0563	-0.0555	-0.0700*
	(0.0231)	(0.0221)	(0.0268)	(0.0266)	(0.0379)	(0.0373)	(0.0356)	(0.0368)
% Seats _held by	-0.456	-0.399	0.976**	1.245**	-0.432	-0.330	-0.434	-0.258
	(0.382)	(0.363)		(0.481)	(0.539)	(0.550)	(0.538)	(0.528)
Gender CM	-0.00261	-	-	-	-0.0306	-0.0310	-	-
	(0.0176)	(0.0175)	(0.0258)	(0.0249)	(0.0248)	(0.0244)	(0.0247)	(0.0243)
Employment rate	0.401	0.352	-0.801	-0.692	-1.004**	-0.909**	-1.339***	-1.158***
	(0.421)	(0.398)	(0.545)	(0.524)	(0.418)	(0.401)	(0.352)	(0.330)
Income per capita	0.701***	0.704***	0.778***	0.765***	0.286**	0.299**	1.110***	1.136***
	(0.103)	(0.0993)	(0.130)	(0.125)	(0.128)	(0.124)	(0.116)	(0.111)
Sex ratio	-0.204**		-0.0154		-0.0687		0.0102	
	(0.0866)		(0.0472)		(0.122)		(0.0788)	
Urban Sex ratio		0.0335		0.0761		0.119		0.0582
		(0.0669)		(0.0779)		(0.100)		(0.0692)
Rural Sex ratio		-0.441***		-		-0.476**		-0.452***
		(0.143)		(0.131)		(0.196)		(0.153)
RC	-2.527**	-0.499	-3.470**	-0.0433	-5.393***	-1.006	-2.658*	0.530
	(1.243)	(0.655)	(1.534)	(1.072)	(2.041)	(1.232)	(1.402)	(0.909)
RC* Literacy rate	-0.293*	0.465*	-0.282	0.0628	0.0219	0.405	0.125	0.237
	(0.149)	(0.258)	(0.197)	(0.427)	(0.260)	(0.470)	(0.121)	(0.235)
RC*% SC	-0.134	0.166	-0.116	-0.138	2.452	2.311	1.044**	0.721
	(0.683)	(0.660)	(0.691)	(0.718)	(1.623)	(1.404)	(0.501)	(0.467)
RC*% ST	-0.319	0.0785	-0.688*	-0.376	-0.273	0.0864	-1.311***	-1.162***

	(0.356)	(0.280)	(0.382)	(0.325)	(0.482)	(0.455)	(0.219)	(0.235)
RC*Police force	-0.937***	-1.002***	-	-0.667**	-0.731	-0.668*	-0.826***	-0.765***
	(0.211)	(0.187)	(0.261)	(0.260)	(0.456)	(0.405)	(0.176)	(0.177)
RC*Sex ratio	1.925		4.186**		4.817		4.948***	
	(1.588)		(1.822)		(2.945)		(1.427)	
RC*% Seats held by	-3.776	-3.826	-2.696	-2.457	-4.611	-4.319	-1.333	-0.690
	(2.571)	(2.558)	(2.682)	(2.626)	(3.615)	(3.464)	(1.425)	(1.584)
RC*Gender CM	-0.0113	-0.0152	-0.0729	-0.0685	-0.162	-0.139	-0.221***	-0.204***
	(0.0582)	(0.0602)	(0.0866)	(0.0874)	(0.138)	(0.143)	(0.0754)	(0.0785)
RC*Employment	-1.379	-0.474	-1.336	0.319	-1.481	0.456	-0.256	1.675*
	(1.063)	(0.754)	(1.131)	(1.019)	(1.425)	(1.305)	(1.062)	(0.888)
RC*Income per	0.593***	0.543***	0.359**	0.319**	0.487***	0.425**	0.190	0.192
	(0.104)	(0.116)	(0.141)	(0.155)	(0.176)	(0.176)	(0.127)	(0.134)
RC* Urban sex ratio		-0.0265		-0.162		-0.404**		0.167
		(0.120)		(0.159)		(0.197)		(0.103)
RC* Rural sex ratio		-0.211		0.103		-0.0270		0.142
		(0.168)		(0.224)		(0.254)		(0.164)
Observations	6,211	6,149	6,211	6,149	6,187	6,128	6,204	6,145
Adj. R-squared	0.792	0.794	0.701	0.709	0.674	0.673	0.830	0.835

Robust standard errors in parentheses clustered at district level. All regressions include district fixed effect, year fixed effect and state fixed effects

*** p<0.01, ** p<0.05, * p<0.1

TABLE 5: ROBUSTNESS TEST USING WEIGHTED REGRESSIONS

	(1)	(3)	(4)	(6)	(7)	(9)	(10)	(12)
Variables	Property crime rate		Violent crime rate		Economic crime rate		Women crime rate	
arrest rate	-0.205***	-0.192***	- 0.323***	- 0.317***	-0.0482**	- 0.0514***	- 0.230***	- 0.237***
	(0.0452)	(0.0459)	(0.0260)	(0.0262)	(0.0194)	(0.0194)	(0.0195)	(0.0196)
RC*arrest rate		0.113		-0.0440		-0.0464*		0.923***
		(0.294)		(0.0477)		(0.0278)		(0.152)
Literacy rate	-0.253	-0.163	-0.0551	0.0418	-0.300*	-0.256	-0.363*	-0.252*

	(0.191)	(0.138)	(0.254)	(0.223)	(0.169)	(0.165)	(0.186)	(0.138)
% SC	1.504	1.066	0.327	-0.282	3.445	2.901	1.810	1.173
	(1.866)	(1.780)	(2.134)	(2.104)	(2.965)	(2.805)	(2.257)	(2.106)
% ST	-0.692	-0.477	-1.470	-1.222	-2.198	-2.047	-1.658	-1.397
	(0.924)	(0.823)	(1.192)	(1.172)	(1.744)	(1.679)	(1.451)	(1.372)
Police force	0.155***	0.147***	-0.0290	-0.0414	0.113***	0.0950**	0.0514	0.0370
	(0.0283)	(0.0289)	(0.0281)	(0.0295)	(0.0407)	(0.0396)	(0.0331)	(0.0339)
% Seats held by women_	-0.605	-0.763*	0.852*	0.582	-0.405	-0.640	-0.623	-0.839
	(0.381)	(0.392)	(0.472)	(0.488)	(0.525)	(0.535)	(0.523)	(0.542)
Gender CM	-0.0672***	-0.0570***	-0.260***	-0.245***	-0.0687***	-0.0516**	-0.183***	-0.163***
	(0.0164)	(0.0173)	(0.0269)	(0.0284)	(0.0235)	(0.0242)	(0.0248)	(0.0250)
Employment rate	0.569	0.668	-0.708	-0.561	-1.072**	-0.941**	-1.095***	-1.011***
	(0.445)	(0.452)	(0.561)	(0.567)	(0.434)	(0.424)	(0.366)	(0.364)
Sex ratio	-0.198**	-0.208**	0.000788	-0.0186	-0.0304	-0.0571	0.0247	0.00598
	(0.0804)	(0.0831)	(0.0515)	(0.0512)	(0.118)	(0.119)	(0.0681)	(0.0680)
RC		-1.005		-3.101**		-3.974*		-2.851*
		(1.740)		(1.527)		(2.139)		(1.518)
RC*Literacy rate		-0.254		-0.269		0.0483		0.160
		(0.174)		(0.206)		(0.270)		(0.129)
RC*% SC		-1.525*		-1.102		1.697		-0.0216
		(0.912)		(0.690)		(1.541)		(0.494)
RC*% ST		-1.056***		-1.163***		-0.745		-1.752***
		(0.382)		(0.363)		(0.481)		(0.209)
RC*police force		-0.0947		-0.112		-0.102		-0.458***
		(0.223)		(0.236)		(0.360)		(0.157)
RC*Sex ratio		2.152		4.691**		5.035		5.290***

		(2.303)		(2.096)		(3.094)		(1.790)
RC*Seats_held by women		-0.471		-0.397		-1.688		0.652
		(2.904)		(2.752)		(3.621)		(1.529)
RC*Gender CM		-0.143		-0.165*		-0.260		-0.315***
		(0.0937)		(0.0988)		(0.159)		(0.0828)
RC*Employment rate		0.185		-0.552		-0.326		0.555
		(1.251)		(1.146)		(1.450)		(1.065)
Observations	6,211	6,211	6,211	6,211	6,187	6,187	6,204	6,204
Adj. R-squared	0.782	0.784	0.696	0.698	0.672	0.676	0.819	0.822

Robust standard errors in parentheses clustered at district level. All regressions include district fixed effect, year fixed effect and state fixed effects

***** p<0.01, ** p<0.05, * p<0.1**

Indian Institute of Management Kozhikode

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Abstract:

The paper has two main goals. First, using district level panel data we examine the key determinants of violent crime, non-violent crimes and crime against women in India for the period 1990-2007. Second, using the district level variation in Maoist conflict, we examine how conflict affects both crime as well as the roles of various determinants of crime. In addition to looking at the conventional determinants of crime (law enforcement and economic variables), we examine how variation in sex ratios affects crime. We also look at whether the gender of the chief political decision maker in each state (i.e. the Chief Minister) affects crime. We find that improvements in arrest rate decrease the incidence of all types of crimes. Socio-economic variables have relatively little explanatory power. We also find evidence that unbalanced sex ratios, in particular in rural areas, may adversely affect crime. Female political representation with greater decision-making power particularly diminishes violent crime and crime against women. Finally, we find a counter-intuitive result that in districts affected by the Maoist insurgency, all types of crime are lower and we offer explanations for why that may be the case.

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