# CRIME AND SOCIAL CONFLICT IN INDIA

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**Abstract**

This article has two goals. First, using district-level panel data we identify key determinants of violent crime, nonviolent crime, and crime against women in India, 1990-2007. Second, using district-level variation in regard to Maoist-driven social conflict, we examine how social conflict affects crime and its determinants. In addition to conventional determinants of crime (e.g., law enforcement and economic variables), we examine how variation in sex ratios affects crime. We also study whether the gender of the chief political decisionmaker in each state affects crime. We find that improvements in arrest rates decreases the incidence of all types of crimes. Socioeconomic variables have relatively little explanatory power. We also find evidence that unbalanced sex ratios, particularly in rural areas, increase crime. The presence of a female Chief Minister diminishes violent crime and, especially, crimes against women. Finally, we find 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.

This article examines patterns of interpersonal crime in India for the period 1990-2007. While analyzing how socioeconomic and demographic factors have affected crime, it adds the novel consideration that crime rates may differ between districts affected by Maoist (Naxalite) violence and those that have remained relatively unaffected by it. The analysis of crime across developing countries often takes a backseat in the face of issues such as poverty and lack of effective governance, but it is increasingly understood that there is a close relationship among interpersonal crime, violent social conflict, and socioeconomic backwardness. Despite its economic advancement, India has been facing various instances of social conflict, and the post-2004 revival of Maoist violence presents a particular challenge both in that it burdens law enforcement and in regard to the longer term effect of changing economic conditions that may have precipitated the social conflicts in the first place.[1]

Factors affecting levels, rates, and patterns of crime may vary across conflict and nonconflict districts for several reasons. First, law and order concerns may lead to an increase in police presence in social conflict areas and thus affect interpersonal crime. Second, the distribution of preferences (e.g., attitudes to risk, tolerance for violence) may differ across the population of conflict and nonconflict areas, which could affect both conflict-related violence as well as criminal behavior. Third, socioeconomic factors are often cited as among the causes of social conflict and even without disentangling the cause-effect issue here, one can still study differences in the impact of some such factors on crime across conflict and nonconflict states. In addition, the distribution of people from different castes varies across states (and there is evidence that this plays a role in violent crime in India) but the role of caste may be particularly strong in states affected by social conflict. Fourth, advances in general literacy may lower crime across all states but may have particularly strong effect in social conflict-ridden areas.[2]

Following the traditional economics of crime literature, we first study the broad pattern and determinants of interpersonal crime for India's 16 major states. We then separate the data into Red Corridor districts (where Maoist violence is prevalent) and non-Red Corridor districts to learn whether any differences emerge. The literature on the crime determinants in India has addressed some of the issues raised in this article. But in one such study the authors do not differentiate among different categories of crime and therefore are unable to address the heterogeneity in crime rates within states. In another study, the author examines crime and Maoist violence but does not explore any mechanism to explain why social conflict may affect crime rates differently in Red Corridor districts than in other districts.[3]

Our choices of the determinants of crime are based on what we believe to be important factors that affect the costs and benefits of committing crime, but we consider two additional India-specific factors that can affect crime. The first of these is the female-to-male sex ratio. Unlike developed countries, which have a stable, naturally balanced sex ratio, Indian states experience considerable variation and imbalance in sex ratios. Second, female political leadership may be expected to affect crime-reporting and enforcement, and particularly in regard to crimes directed against women.

The next section provides a brief background of the Maoist insurgency, followed by a discussion of data, empirical strategy, results, and a concluding section.[4]

## Social conflict in India

India is home to a number of social conflicts at the sub-national level. Measured by intensity, the main ones are the Maoist movement, the Hindu-Muslim communal conflict, various separatist movements in the northeastern states, and Islamic fundamentalist terrorism. These are spread across the country and vary substantially in their magnitude of incidence.[5]

In this article we focus on the Maoist conflict, India's longest-running. It is considered the country's major internal social conflict and its control and eventual cessation is high on the central government's agenda. Among the motives behind the start and diffusion of this social conflict are unequal land distribution and insecure land rights, which mostly affect lower castes and ethnic tribal groups. The land-related social conflict started in 1967 in the village of Naxalbari in West Bengal and spread due to underdevelopment itself and due to the support gained from political parties such as the Communist Party of India (Marxist). For much of its existence, the Naxalite insurgency was highly fragmented, consisting of numerous ideologically opposed groups. It was not until 2004 that its two major groups merged, forming the Communist Party of India (Maoist). This was the starting point of neo-Naxalites and is, for us, the starting point of our analysis. The intensity of this social conflict is highly heterogeneous both across districts within affected states as well as across states.[6]

The general literature suggests that social conflict adversely affects economic growth. This has been shown to hold for Naxalite-affected districts, which are among the poorest in India. Among the major causes that underpin the Naxalite-related unrest are institutional and colonial legacies that cause underdevelopment in the affected districts. Another strand of the literature establishes that adverse climate shocks (or adverse natural resource shocks) increase the intensity of social conflict. The underlying mechanism is that adverse climate shocks are correlated with income shocks. These can intensify social conflict in the form of fighting over resources to alleviate income constraints. Still other authors point to strategic elements. For example, areas suffering adverse climate shocks may be strategically chosen by Maoist insurgents as target areas for conflict.[7]

**This article studies patterns of interpersonal crime in India for the period 1990-2007. While analyzing how socioeconomic and demographic factors have affected crime, it adds the novel consideration that crime rates and crime determinants may differ between districts affected by Maoist (Naxalite) violence and those that have remained relatively unaffected by it. We find that crime is generally lower in districts affected by Naxalite insurgents.**

Abstracting from the cause or causes of the Maoist conflict, we instead ask what role Maoist-driven conflict may have had on various types of interpersonal crime, for example, through policies implemented to control the insurgency. This is important, first, because conflict states may experience higher crime, particularly violent crime, precisely because of the insurgency and, second, by lowering economic growth, social conflict may reduce the opportunity cost of committing nonviolent crime. 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 interpersonal crime in general. The conflict also has led to an increased military presence in affected states which may have the unintended consequence of lowering rates of interpersonal crime.

Similar to a 2012 paper which addresses the potentially positive consequence of counterinsurgency policies for economic growth, our analysis points to a related conclusion: Our estimates suggest that districts that experience Maoist conflict, interpersonal crime has decreased due to improved policing.[8]

## Data and empirical strategy

Our empirical specification is given by the following equation:

$$(1)\quad C_{d,s,t} = \beta_0 + X^1_{d,t}\beta + X^2_{s,t}\beta + \delta_d + \mu_t + \varepsilon_{d,s,t} \ ,$$

where $C_{d,s,t}$ is the logarithm of the crime rate per 100,000 population in district *d* of state *s* at time *t*. $X^1$ is a vector of district-specific socioeconomic explanatory variables, and $X^2$ is a vector of state-specific variables. The error-term is given by $\epsilon_{d,s,t}$. Crime and violence rates may depend on unobservable factors, such as social norms and tolerance of crime, that are persistent through time and which can vary across districts. As a result, we include district fixed-effects to account for time-invariant characteristics, $\delta_d$. We also include time-fixed effects to account for national time-variant effects on crime, $\mu_t$. In all regressions, we use robust standard errors clustered at the district-level to address problems of serial correlation and to allow for heteroskedasticity.

Indian states have independent decisionmaking 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 capita. We expect that an increase in deterrence decreases crime. However, allocation of police resources may not be homogenous within states. District-specific characteristics and special interests such as electoral goals and location of firms may lead to heterogeneous allocation of security goods. But data on district-level deterrence measures is not available and thus we include these measures only at the state level. Unobservable time-varying and time-invariant factors that could influence the allocation of resources are captured by the inclusion of ($\delta_d + \mu_t$).

We collected district level data on 16 crime categories from the National Crime Records Bureau (NCRB). Using these, we grouped crime into four major groups as defined by the Indian Penal Code. They are: (1) violent crime, (2) property crime, (3) economic crime, and (4) crimes against women. The crime data are commingled and do not allow us to identify crime directly attributable to the Maoist insurgency. For the 16 states, we altogether construct a data panel for 346 districts for the years 1990 to 2007. In addition, to obtain measures for law enforcement, we use state level data on police strength per capita (civil and armed) and arrest rates per category. As mentioned, 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 1991 and 2001 censuses. 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 issued by 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 in Table A1.[9]

The Government of India's Reimbursement of Security Related Expenditures (SRE) scheme identifies the districts that have been affected by the Naxalite conflict (evaluated by the intensity of the conflict). The central government released Rs. 5 billion (approximately USD80 million) to affected state governments reimbursing them for expenditures incurred as of fiscal year 2004-2005. These include reimbursement for expenditures related 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."[10]

We use the SRE information to construct a Red Corridor dummy variable. Among the 16 states in our sample, seven have districts affected by the Naxalite conflict. We use the report produced by the Ministry of Home Affairs to construct a dummy variable for districts affected by the Naxalite insurgency, post-2004. This gives us a total of 46 districts that are considered conflict-affected areas, as per the 1990 boundaries. This measure is imperfect as it does not capture the intensity of the social conflict or the expansion of the insurgency since its inception. However, it is a useful summary measure of social conflict.[11]

We employ the following specification to estimate the marginal impact of being in a Naxalite-affected state:

$$\begin{aligned}C_{d,s,t} &= \beta_0 + X^1_{d,t}\beta + X^2_{s,t}\beta + X^1_{d,t}\beta \times RC_{d,t} \\ &\quad + X^2_{s,t}\beta \times RC_{d,t} + \beta_k RC_{d,t} + \delta_d + \mu_t + \varepsilon_{d,s,t}\end{aligned} \quad , \tag{2}$$

which augments equation (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 equation (1) and $RC_{d,t}$ is a (Red Corridor) dummy variable for districts affected by Naxalite conflict, post-2004. This specification explicitly tests for the differential effect of the social conflict on factors determining crime. Results are presented in Tables A3 and A4, to be discussed shortly. A concern in all these specifications is the potential for multicollinearity among the variables. We conducted variance inflation checks which suggest that this is not an issue.

One final concern to address is underreporting. Police-recorded crimes depend on reporting levels and, as a result, some crimes may be left unreported or there can be differences in reporting behavior across states. Underreporting may not be uniform and the probability of reporting can be influenced by factors such as perceptions of policing and citizen empowerment, which may vary across states. Further, the NCRB data consider only the principal crime (i.e., the highest recorded offence). Thus, it is likely that our estimates are affected by underreporting bias. It is of course possible that (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 here.[12]

We address these concerns in two ways. First, district fixed-effects control for time-invariant, district-specific factors. As long as such fixed district-specific factors cause persistent underreporting of crime in a district, the inclusion of fixed effects should mitigate some of the concerns over crime misreporting. Second, in equations (1) and (2), richer states may show higher crime rates due to different reporting behavior or different incentives to commit crimes (e.g., 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 equation (2) using the inverse of the income level as the weight. Thus, richer states have lower weight than poorer states. Results are reported in Table A4.[13]

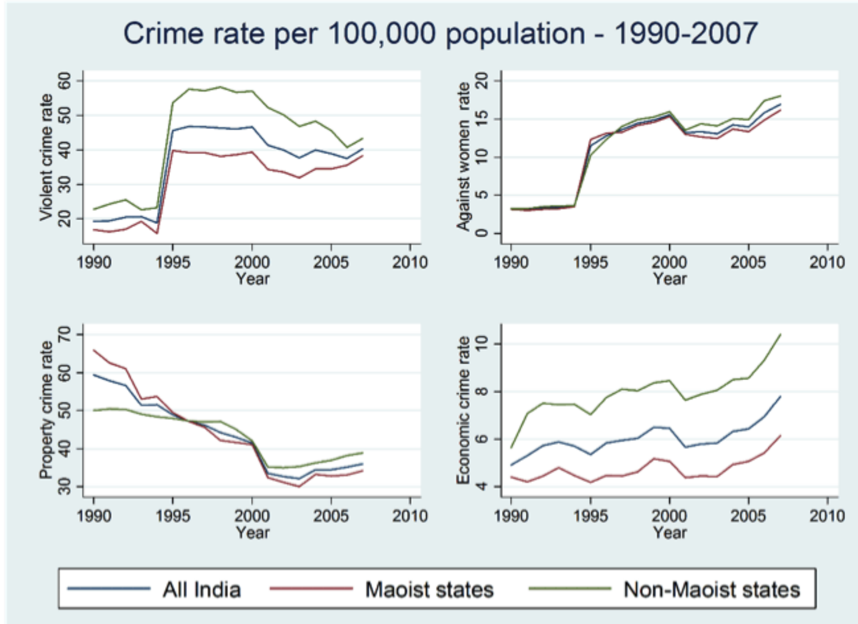


**Figure 1**: Trends in crime categories in India.

## Results

Table A1 presents the definitions, geographic reach, and data sources of all variables included in our estimations. Table A2 presents the descriptive statistics. Areas affected by Maoist conflict are statistically different from nonconflict areas. Crime rates are higher in nonconflict states in comparison to conflict states. Arrest rates are higher in conflict states but police force per capita is lower. Note that in conflict states the police force is supplemented by paramilitary forces, but our measure of law enforcement in conflict states does not account for these additional forces since detailed data are unavailable.[14] Figure 1 depicts the trends in the four crime categories across all-India, Maoist, and non-Maoist states. It is striking to see that while property crime has decreased since the economic liberalization reforms of 1991, violence has increased. Economic crime has also increased but at a level much lower than violent crime. Property crime has decreased faster in Maoist states than in non-Maoist states. Similarly, violence and economic crime rates have been following the same trend as the rest of India although with lower rates.

Table A3 presents the main results. In the very first line, the reported coefficients suggest that crime rates across all crime categories are lower in Red Corridor districts than in other districts. All the other lines in Table A3 report the results by crime determinant and its interaction term with Red Corridor districts. Thus, in the first 2 lines, all arrest rate coefficients are negative and statistically significantly different from zero across all crime categories. A 1 percent increase in arrest rates is interpreted to decreases property crime by approximately 0.19 percent (column 1), violent crime by approximately 0.32 percent (column 3), economic crime by 0.06 percent (column 5), and crime against women by 0.21 percent (column 7). The marginal (interaction) effect of arrests on crime in Red Corridor (RC) districts is not statistically significant across the crime categories except for the case of crimes against women in which higher arrest rates in Red Corridor districts are statistically associated with *increased* violence against women.

The potential deterrent effect of the police force is mixed. For violent crime and crime against women, higher police force levels decrease both crimes, and more so in Red Corridor districts. For the nonviolent crimes—property and economic crime— the effect is that larger police forces are associated with *more* crime but in Red Corridor districts the marginal effect is toward fewer such crimes. This might be capturing the effects of increased paramilitary forces in these areas as well as the increased efforts to control the social conflict in the region. Although this differential impact of policing on crime between social conflict and nonconflict areas may also be picking up reverse causality, lagged values for police force give similar results. The positive coefficient of police force in nonconflict areas could also come from the fact that higher police force levels may lead to more nonviolent crime being recorded in the first place (a police force short on staff may not take these crimes seriously). Since our definition of Red Corridor districts is based on the GOI definition, these areas are known to have an increased police and paramilitary presence, lending credence to our hypothesis that this may be contributing to the lower crime rate.

The role of female political participation is ambiguous and depends on the level of decisionmaking 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 a woman as Chief Minister decreases violent crime and crime against women. The effect is consistent across specifications, and when estimating the effects across conflict states, the role of a woman Chief Minister in reducing crime against women turns out to be especially stronger.

An increase in employment rates reduces economic crime and crime against women. This result is also consistent across specifications. Higher income per capita increases crime for all categories. This is consistent with the fact that in India an increase in income has increased inequality which may increase crime. 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 the Red Corridor dummy.[15]

The classic theory of crime suggests that criminals engage in illegal activity as an occupational choice or human capital investment opportunity. Individuals decide on whether or not to commit crime based on the expected utility of engaging in criminal activity as opposed to investing in education or legitimate work. Thus, the effect of increased numbers of literates is expected to reduce crime. We do not find evidence of this in the context of our data.

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, although Table A3 does show that a higher share of ST population is statistically associated with increased levels of economic crime and crime against women.

We expect that female-to-male sex ratios have an inverse relation to crime given that the propensity of males to commit crime is higher than that for females. Our results show that this inverse relation holds consistently only in rural areas, and that there is no general additional statistically significant effect in the Red Corridor areas.[16]

Finally, note that the results from the weighted regressions (Table A4) are qualitatively unchanged from the results in Table A3. This suggests that our main findings are not driven by states of a particular economic size, rich or poor.

## Conclusion

Our analysis of interpersonal crime and social conflict in India shows that deterrence in the form of arrest rates matters in lowering crime and that socioeconomic variables do not systematically influence crime. However, this blanket statement can now be qualified in several important respects. First, the presence of a female state Chief Minister is statistically associated with reduced crime against women specifically and violent crime generally. Second, we find that social norms and practices that continue to skew the female-to-male sex ratio partly explains why violent crime against women continues to rise. In regard to Maoist-driven violence, we find that Red Corridor states have statistically significantly *lower* crime rates as compared to states that are unaffected by the insurgency. We find this intriguing and hope that future work will examine whether this finding is due to larger expenditures on law enforcement with paramilitary forces complementing the police or whether Maoist dominance mitigates interpersonal crime in these states. If it is the former, then this would suggest that expenditure on law enforcement to reduce social conflict may have a diffusion effect in reducing crime in general. While our results point toward this possibility, more research is needed to arrive at firm conclusions.

## Notes

1. On Maoists/Naxalites: See, e.g., Kujur (2008). The terms are used interchangeably in this article. On the connections among conflict, crime, and socioeconomic development: See, e.g., HRW (2008); Ramaiah (2011); Demombynes and Ozler (2005); Hoelscher, Miklian, and Vadlamannati (2013).

2. Caste and crime: Ramaiah (2011); Dutta and Husain (2009). Literacy and crime: Machin, Marie, and Vuji (2011).

3. Traditional literature: That is, the literature since Becker (1968). As per the 2001 census, India's 16 major states hold more than 90 percent of its population. We do not consider the least populous states because these do not have consistent crime statistics. One study: Dutta, Husain (2009). Another study: Borooah (2008).

4. Female decisionmaking: Iyer, *et al*. (2012).

5. Intensity: Gomes (2012). Less intense social conflicts and insurgencies include for example the Tamil insurgency movement.

6. Central government agenda: In 2006, India's Prime Minister stated that the Maoist conflict was "the single biggest internal security challenge ever faced by our country." ("Ending the Red Terror." *The Economist*. 25 February 2010). Land rights and distribution: Kujur (2008); Gomes (2012); Iyer (2009). Fragmented Naxalites: Kujur (2008). Heterogenous: Eynde (2013).

7. Miguel and Satyanath (2011); Bholken, Sergenti, and John (2010). The poorest states: Iyer (2009). Institutional and colonial legacies: Gomes (2012). Climate shocks: Bholken, Sergenti, and John (2010). Strategic elements: Eynde (2013).

8. Positive: Singhal and Nilakantan (2012).

9. 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.

10. SRE: GOI (2004); Iyer (2009). Quote: Naxalite Management Division, Ministry of Home Affairs, Government of India.

11. Conflict states: Considering the 1990 borders, the Naxalite-affected states are Andhra Pradesh, Bihar, Madhya Pradesh, Maharashtra, Orissa, Uttar Pradesh, and West Bengal. Ministry of Home Affairs: GOI (2004).

12. Probable underreporting: Prasad (2013).

13. It is worth noting that work comparing reported and self-reported crimes in India shows that even if crime is underreported, the use of police-reported statistics is still informative (see Prasad, 2013).

14. Iyer (2009) mentions that an extra 33 battalions of central paramilitary forces and 32 battalions from the Indian Reserve Force have been deployed to conflict-affected states in order to increase personnel per capita.

15. Increased income inequality and crime: Bandyopadhyay (2011).

16. Crime propensity of males: This general propensity is noted by several researchers, see, e.g., Bennett, Farrington, and Rowell Huesmann (2004). Edlund, Li, Yi, and Zhang (2013) analyze the impact of varying sex ratios on crime for China, the only other country where this specific analysis has been done.

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**Table A1: Definitions of variables**

| *Variable* | *Definition. Geographic level. Source.* |
|---|---|
| Property crime rate | Total incidents per 100,000 population. Includes incidents registered under burglary, robbery, theft, and dacoity. District-level. NCRB yearly reports. |
| Violent crime rate | Total incidents per 100,000 population. Includes 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 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 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. |

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**Table A2: Descriptive statistics**

| | All | Non-Maoist states | | Maoist States | | Difference * | |
|---|---|---|---|---|---|---|---|
| *Variables* | *Mean* | *SD Mean* | *SD* | *Mean* | *SD* | | |
| 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*** |
| Crimes against women 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*** |
| Crimes against women arrest rate | 0.45 | 0.30 | 0.44 | 0.30 | 0.52 | 0.30 | -0.08*** |
| Police force per capita | 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 |
| Red Corridor (RC) | 0.03 | 0.17 | 0.00 | 0.00 | 0.22 | 0.41 | -0.220*** |

*Notes*: * Difference in means tests between non-Maoist and Maoist areas. Statistically significant differences at the 1%, 5%, and 10% levels are marked as ***, **, *, respectively.

### Table A3: Crime and conflict

| *Variable* | (1) *Property crime rate* | (2) | (3) *Violent crime rate* | (4) | (5) *Economic crime rate* | (6) | (7) *Crimes against women rate* | (8) |
|---|---|---|---|---|---|---|---|---|
| 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) |
| Arrest rate | -0.188*** | -0.199*** | -0.320*** | -0.327*** | -0.055*** | -0.0569*** | -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) |
| Police force | 0.0862*** | 0.0772*** | -0.104*** | -0.120*** | 0.0689* | 0.0563 | -0.0555 | -0.0700* |
| | (0.0231) | (0.0221) | (0.0268) | (0.0266) | (0.0379) | (0.0373) | (0.0356) | (0.0368) |
| RC*Police force | -0.937*** | -1.002*** | -0.689*** | -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) |
| % Seats women | -0.456 | -0.399 | 0.976** | 1.245** | -0.432 | -0.330 | -0.434 | -0.258 |
| | (0.382) | (0.363) | (0.493) | (0.481) | (0.539) | (0.550) | (0.538) | (0.528) |
| RC*% Seats women | -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) |
| Gender CM | -0.00261 | -0.0000597 | -0.184*** | -0.184*** | -0.0306 | -0.0310 | -0.0722*** | -0.0729*** |
| | (0.0176) | (0.0175) | (0.0258) | (0.0249) | (0.0248) | (0.0244) | (0.0247) | (0.0243) |
| 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) |
| 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) |
| RC*Employment rate | -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) |
| 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) |
| RC*Income per capita | 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) |
| 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) |
| 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) |

## Table A3: Crime and conflict (continued)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Variable* | *Property crime rate* | | *Violent crime rate* | | *Economic crime rate* | | *Crimes against women rate* | |
| % 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) |
| 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) |
| % 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) |
| 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) |
| Sex ratio | -0.204** | | -0.0154 | | -0.0687 | | 0.0102 | |
| | (0.0866) | | (0.0472) | | (0.122) | | (0.0788) | |
| RC*Sex ratio | 1.925 | | 4.186** | | 4.817 | | 4.948*** | |
| | (1.588) | | (1.822) | | (2.945) | | (1.427) | |
| Urban sex ratio | | 0.0335 | | 0.0761 | | 0.119 | | 0.0582 |
| | | (0.0669) | | (0.0779) | | (0.100) | | (0.0692) |
| RC* Urban sex ratio | | -0.0265 | | -0.162 | | -0.404** | | 0.167 |
| | | (0.120) | | (0.159) | | (0.197) | | (0.103) |
| Rural sex ratio | | -0.441*** | | -0.612*** | | -0.476** | | -0.452*** |
| | | (0.143) | | (0.131) | | (0.196) | | (0.153) |
| 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 |

*Notes*: Robust standard errors in parentheses are clustered at district level. All regressions include district and year fixed effects. Coefficients statistically significant at the 1%, 5%, and 10% levels are marked with ***, **, *, respectively.

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**Table A4: Robustness test using weighted regressions**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Variable* | *Property crime rate* | | *Violent crime rate* | | *Economic crime rate* | | *Crimes against women rate* | |
| RC | | -1.005 | | -3.101** | | -3.974* | | -2.851* |
| | | (1.740) | | (1.527) | | (2.139) | | (1.518) |
| 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) |
| 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) |
| RC*Police force | | -0.0947 | | -0.112 | | -0.102 | | -0.458*** |
| | | (0.223) | | (0.236) | | (0.360) | | (0.157) |
| % Seats 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) |
| RC*Seats women | | -0.471 | | -0.397 | | -1.688 | | 0.652 |
| | | (2.904) | | (2.752) | | (3.621) | | (1.529) |
| 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) |
| RC*Gender CM | | -0.143 | | -0.165* | | -0.260 | | -0.315*** |
| | | (0.0937) | | (0.0988) | | (0.159) | | (0.0828) |
| 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) | (0.43) | (0.424) | (0.366) | (0.364) |
| RC*Employment rate | | 0.185 | | -0.552 | | -0.326 | | 0.555 |
| | | (1.251) | | (1.146) | | (1.450) | | (1.065) |
| 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) |
| RC*Literacy rate | | -0.254 | | -0.269 | | 0.0483 | | 0.160 |
| | | (0.174) | | (0.206) | | (0.270) | | (0.129) |
| % 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) |
| RC*% SC | | -1.525* | | -1.102 | | 1.697 | | -0.0216 |
| | | (0.912) | | (0.690) | | (1.541) | | (0.494) |

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**Table A4: Robustness test using weighted regressions (continued)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Variable* | *Property crime rate* | | *Violent crime rate* | | *Economic crime rate* | | *Crimes against women rate* | |
| % 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) |
| RC*% ST | | -1.056*** | | -1.163*** | | -0.745 | | -1.752*** |
| | | (0.382) | | (0.363) | | (0.481) | | (0.209) |
| 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*Sex ratio | | 2.152 | | 4.691** | | 5.035 | | 5.290*** |
| | | (2.303) | | (2.096) | | (3.094) | | (1.790) |
| 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 |

*Notes*: Robust standard errors in parentheses are clustered at district level. All regressions include district and year fixed effects. Coefficients statistically significant at the 1%, 5%, and 10% levels are marked with ***, **, *, respectively.