# Effects of Political Dissent on Crime: Evidence From India

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## 1 Introduction

Elections often lead to a contentious political atmosphere. For people in these communities, their ramifications can be significant; their safety or economic well-being could be affected by their result. From Bolivia to Pakistan, tensions between political parties have boiled over to deaths and general instability. In India, political violence prior to and during its election process is not unprecedented. During the 2014 Indian election, over 2000 political workers were injured; 16 were killed (Rawat 2019).

Much analysis has been done on the impact of election outcomes on local communities. Asher and Novosad (2017) utilize a close election discontinuity to measure the impact of political favoritism; constituencies with representatives in government experienced increased growth in night lights and job creation relative to areas led by opposition parties. Outside of India, Levitt (1997) utilizes police hiring variation in election-years to analyze the effects of police on violent crime. That paper found significant declines in violent crime within election years, but little changes in property crime rates.

Shocks in economic activity have also been shown to affect crime rates. Blakeslee and Fishman (2017) find that negative rainfall and positive temperature shocks are positively associated with burglaries and riots in Southeast Asia. Within India, an increase in the frequency in riots precludes a statistically significant increase in the vote share of the BJP (Iyer and Shrivastava 2018).

In this paper, I estimate the effects of elections on my outcome variables: property and violent crime rates. From outcomes of national and state parliamentary elections, I also analyze the effect of political dissent on crime. Vote share of the ruling parties is used as a proxy for potential discontent with the election outcome. This paper will also identify effects of economic development on the frequency of criminal activity. I hypothesize that political tensions, which are brought to the forefront during these election periods, result in an increase in crime within those years.

## 2 Data

To construct this dataset, several datasets were merged at the state level. Data regarding night light intensity were developed by the National Oceanic and Atmospheric Administration. That data was geocoded within political boundaries by Asher and Novosad (2017), which is accessible through their SHRUG dataset.

I downloaded national election results from a dataset compiled by Bhavnani (2014). Outcomes of all Lok Sabha (India's lower house of parliament) races are included for elections from 1991-2004 and 2014. Results from the 2009 election are not present in this dataset.

For the district-level specification, state assembly election results were downloaded from the Lok Dhaba repository, which is maintained by the Trivedi Centre for Political Data. Using their attribution of political constituencies to districts for elections after 2007, I created a balanced panel of 280 districts within India (about half of all districts). Instead of crime rates the district-level dataset uses actual crime counts: yearly population estimates could not be found for these districts.

Crime data used in this analysis were transcribed from reports released of India's Ministry of Home Affairs. It includes national, state, and district counts of various crimes from 1954-2006. I use state-level counts of murders, riots, and dacoities (banditry). The outcome variables for the state-level specification are normalized to rates per 100000 inhabitants. State-level police strength and annual population estimates are also available for years 1969-2006.

## 3 Empirical Specification

From the data, I create a empirical specification that analyzes how national elections affect crime within states. The regression is as follows:

$$ln(crime_{it}) = \alpha_0 + \delta_1 election_t + \delta_2 year_i + \theta \mathbf{X}_{it} + a_i + \epsilon_{it}$$

$i$ and $t$ signify the state and year respectively. $crime_{it}$ is our crime variable of interest, which in this case can be murder, rabboery, or riots rates per 100000 persons. $election_t$ is an indicator variable, where it is 1 if an election takes place in year $t$. $\mathbf{X}_{it}$ is a vector of control variables, which can account for changes in police strength and economic activity. $a_i$ is a state fixed effect. $\epsilon_{it}$ is the residual error clustered by state and time.

To analyze the effect of political dissent within states, I include the proportion of vote share for parties in power. A second specification includes the vote share of parties in the subsequent government. The second regression is:

$$ln(crime_{it}) = \alpha_0 + \delta_1 voteshare_{it} + \delta_2 year_i + \theta\mathbf{X}_{it} + a_i + \epsilon_{it}$$

$\frac{\delta_1}{100}$ is the estimated effect on crime of a 10% increase in vote share of parties in the incoming government. We include a time trend $year_i$ within this specification to account for the overall decrease in Indian crime rates during the time period of interest.

Figure 1 is a scatter plot of national crime rates from 1994-2006. For all categories of reported crimes analyzed, there is a significant, constant decline over time. There is a 25% decrease in the murder rate per 100,000 inhabitants during this period. Figure 1 also indicates that there is a 50% decrease in the occurrence rates of riots and dacoities from 1994 to 2006.

In a similar manner to the state specifications above, I estimate the effects of crime on districts, which provides more detail to where these crimes are taking place within a state. For measuring the impact of an election-year of district crime, I use this specification:

$$crime_{it} = \alpha_0 + \delta_1 election_t + \theta\mathbf{X}_{it} + a_i + a_t + \epsilon_{it}$$

$i$ and $t$ signify the district and year respectively. District and time fixed effects are used to mitigate the effects of rising populations within this time period. For electoral dissent, the regression is:

$$crime_{it} = \alpha_0 + \delta_1 voteshare_{it} + \theta\mathbf{X}_{it} + a_i + \epsilon_{it}$$

Since I do not have data on state assembly coalitions, determining the winning political parties for these elections is not as clear-cut. In this case, I define the winning coalition as the parties currently in government at the *national level*.

## 4 Results

I show that election years and the opposition to the winning political faction have no significant effect on state-level crime rates. Results for the first model are in Table 3A, which does not account for election outcomes. After including a time trend, there was no significant effect of elections on crime rates of all types. In Table 3A, the intensity of night lights is positively associated with an increase in the rate of dacoities.

From the estimate, a unit increase in average light frequency (measured 0-64) is associated with a 10.5% increase in robberies. This result suggests that wealthier states are associated with a greater frequency of robberies. However, this result does not account for the proportion of urban inhabitants within each state.

Police strength is strongly correlated with the rate of murders and riots. From those significant estimates, it would be more reasonable to say that states with more crime have a stronger police force: not the reverse. National election political dissent does not appear to significantly affect crime rates (as shown in Table 3B).

District-level results show a minimal effect of being in an election year on crime rates. In Table 4A, election years did not have significantly increased crime frequencies for any of the three types. However, increased light intensity appears to be significantly associated with murder counts at the 1% level, with a unit increase in light intensity is associated with 3.5 more annual murders in a district.

When measuring the effect of incumbent government support, the result is similar (Table 4B). There does not appear to be a significant effect of political attitudes on crime, according to the definition used here. While light intensity does not have a significant affect on murder counts, its negative effect on riots is significant at the 90% level. A unit decrease in light intensity is associated with a decrease of 30 riots within a district. This may be due to the way riots are measured; the frequency is what is important, not their intensity or number of persons involved.

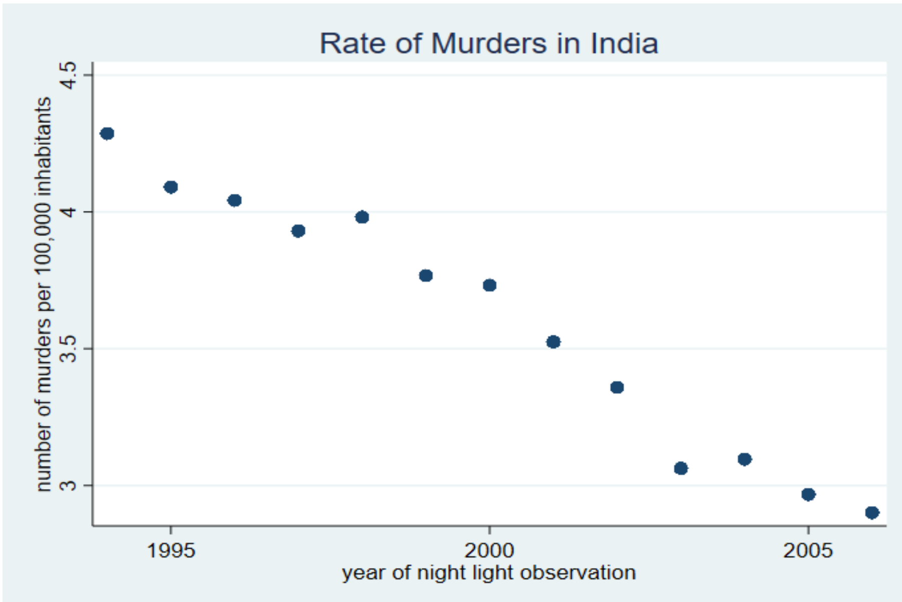
## 5 Conclusion

From this regression, we cannot isolate the effects of elections on politically unstable states, which may be more unstable due to religious or caste demographics. Neither level of analysis has taken demographics of that sort into account. Further controls, like demographics, should be added in order to avoid omitted variable bias. It is unlikely that light intensity and election outcomes are the sole drivers of crime, especially at the district level.

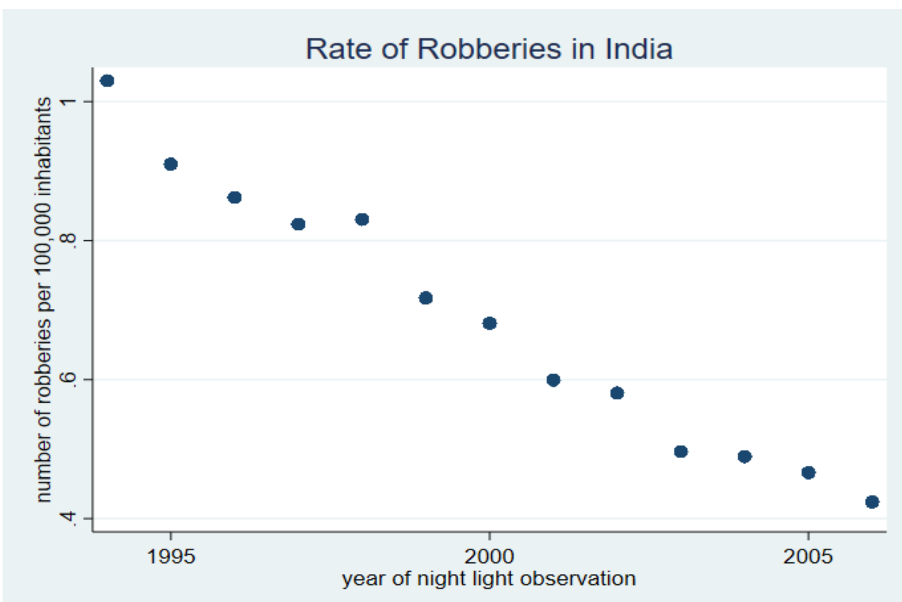
While I was able to aggregate electoral results into districts, there are still issues with this methodology. First, the determination of what constitutes political opposition is not always precise, particularly for the district-level analyses. Election results could oppose national outcomes, but not the parties in power in the state assemblies. My analysis ignores that discrepancy for now, but further research can adjust what constitutes support for the opposition.

From these results, I can conclude that crime of all categories has significantly declined over time in India. Police force strength tends to be larger in states with higher murder rates, but are not positively associated with other types of crime. From our state-level analyses, there does not appear to be a national election effect on crime within states. Similar analyses using state elections show that election administration nor support for national politicians affect district crime levels.

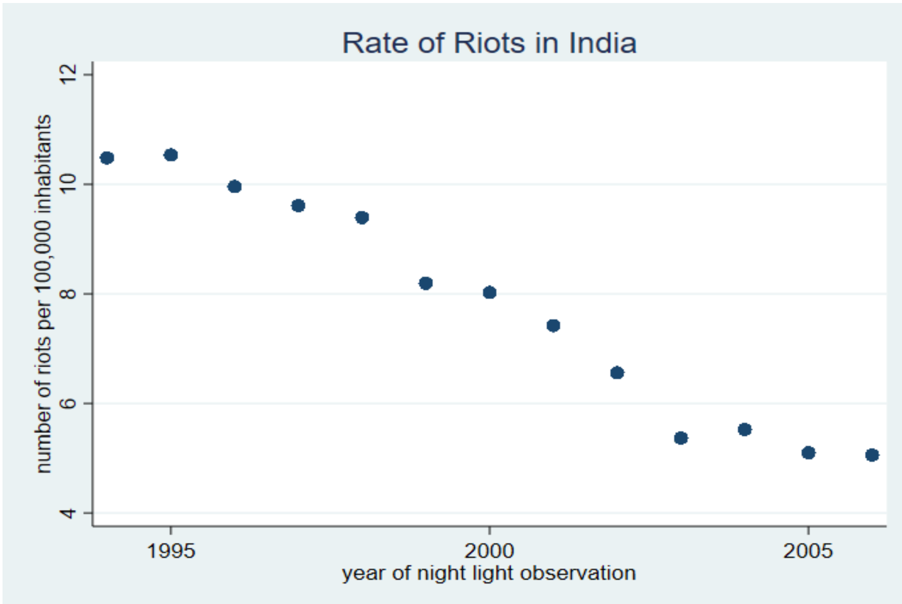
**Figure 1: Crime Rate Scatter Plots (1994-2006)**




*Note:* The y-axis plots the national rate of murders per 100,000 inhabitants for years 1994-2006. Population estimates come from the "Crime in India" dataset, which produce state-level estimates for each year within the interval.




*Note:* The y-axis plots the national rate of robberies per 100,000 inhabitants for years 1994-2006. Population estimates come from the "Crime in India" dataset, which produce state-level estimates for each year within the interval.




*Note:* The y-axis plots the national rate of riots per 100,000 inhabitants for years 1994-2006. Population estimates come from the "Crime in India" dataset, which produce state-level estimates for each year within the interval.

**Table 2A: District-Level Summary Statistics**

| | Obs. | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Light Intensity | 548 | 4.415 | 4.387 | 0 | 50.56 |
| Govt Support | 548 | 35.784 | 15.375 | 0 | 96.354 |
| Murders | 548 | 68.906 | 62.784 | 0 | 542 |
| Robberies | 548 | 12.170 | 17.650 | 0 | 169 |
| Riots | 548 | 133.213 | 184.906 | 0 | 2520 |

This table shows summary statistics of crime rates, support for the *incumbent* government, and controls for the district-level specification.

**Table 2B: State-Level Summary Statistics**

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| Light Intensity | 8.749 | 13.727 | .030 | 59.914 |
| Winning Coalition Share | .399 | .180 | 0 | .799 |
| Murder Rate | 3.961 | 2.270 | 0 | 14.186 |
| Robbery Rate | .901 | 1.472 | 0 | 20 |
| Riots Rate | 7.690 | 7.989 | 0 | 57.812 |
| Police Strength | 40774.18 | 41195.27 | 204 | 169774 |

This table shows summary statistics of crime rates, support for the *winning* political coalition, and controls for the state-level specification. All rates are crime counts per 100000 inhabitants.

**Table 3A: Election Year Effects on ln(crime)**

| | Murders | Robberies | Riots |
|---|---|---|---|
| Light Intensity | 0.020 | 0.105*** | -0.035 |
| | (0.010) | (0.024) | (0.027) |
| Election Year | -0.019 | -0.016 | 0.090 |
| | (0.023) | (0.055) | (0.062) |
| Police Strength | 0.001*** | 0.000 | 0.001* |
| | (0.000) | (0.000) | (0.000) |
| Year | -0.030*** | -0.082*** | -0.048*** |
| | (0.003) | (0.008) | (0.009) |
| _cons | 59.998*** | 161.552*** | 96.895*** |
| | (6.346) | (15.219) | (17.162) |

This table shows regression estimates for the effects an election has on log crime rates within that a state in a given year. State fixed effects are included. The outcome variables are indicated in the table's columns. Stars represent effect significance at the 90%, 95%, and 99% levels. Values in parentheses are effect standard errors.

**Table 3B: Effect of Ruling Alliance Vote Share on ln(crime)**

| | Murders | Robberies | Riots |
|---|---|---|---|
| Light Intensity | -0.041 | -0.055 | -0.059 |
| | (0.029) | (0.096) | (0.070) |
| Winning Coalition Share | 0.102 | -0.269 | 0.201 |
| | (0.131) | (0.266) | (0.315) |
| Police Strength | 0.001*** | 0.001 | 0.001 |
| | (0.000) | (0.001) | (0.001) |
| Year | -0.021** | -0.079*** | -0.046** |
| | (0.007) | (0.016) | (0.017) |
| _cons | 43.941** | 157.857*** | 94.259** |
| | (14.326) | (30.916) | (34.513) |

This table shows regression estimates for the effects of a state's electoral support for the winning government on log crime rates within that year. State fixed effects are included. The outcome variable for each estimate is indicated in the table's columns. 0.000 standard errors are not exactly zero; this is due to the police strength variable being transformed to the strength per 100000 inhabitants. Stars represent effect significance at the 90%, 95%, and 99% levels. Values in parentheses are effect standard errors.

**Table 4A: Election Year Effects on District Crime Counts**

| | Murders | Robberies | Riots |
|---|---|---|---|
| Light Intensity | 3.506*** | .275 | -3.171 |
| | (.435) | (.199) | (2.453) |
| Election Year | .051 | .427 | -2.290 |
| | (.884) | (.405) | 4.985 |
| _cons | 53.421*** | 10.891*** | 147.568*** |
| | (1.949) | (.894) | (10.987) |
| N | 3640 | 3640 | 3640 |

This table shows regression estimates for the effects an election has on crime *counts* within a district in a given year. District-time fixed effects are included. The type of crime being estimated is indicated in the table's columns. Stars represent effect significance at the 90%, 95%, and 99% levels. Values in parentheses are effect standard errors.

**Table 4B: Effect of Ruling Alliance Vote Share on District Crime Counts**

| | Murders | Robberies | Riots |
|---|---|---|---|
| Light Intensity | 1.287 | .894 | -29.771* |
| | (1.883) | (.909) | (12.267) |
| Govt Support | -.161 | .070 | -.820 |
| | (.103) | (.050) | (.674) |
| _cons | 72.887*** | 6.539 | 316.005*** |
| | (9.564) | (4.618) | (62.313) |
| N | 548 | 548 | 548 |

This table shows regression estimates for the effects of a district's electoral support for the incumbent national government on district crime frequency. District-time fixed effects are included. The type of crime being estimated is indicated in the table's columns. Stars represent effect significance at the 90%, 95%, and 99% levels. Values in parentheses are effect standard errors.

## References

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