Essays on Political Economy and Governance

Shruti Lakhtakia



Exeter College
University of Oxford

A thesis submitted for the degree of
Doctor of Philosophy in Public Policy

Michaelmas 2021

ABSTRACT

This article-based thesis aims to study political economy and governance in developing countries through the lens of crime, policing, and politics.

Chapter 2 studies the impact of election timing on crime and the nature of law enforcement in a developing country known for electoral violence. Using administrative crime data from India in the 2008-2019 period, I undertake fixed effects and difference-in-differences analyses, and provide detailed and rigorous causal evidence for change in the nature of crime and the composition of policing effort as elections approach. I show that upcoming elections increase crimes against public order while reducing crimes against individuals, such as those related to bodily offences, property, or women. I suggest that these cycles are driven by changes in police behaviour – as elections approach, the police sharply increase preventive activity and the enforcement of crimes related to public order, and reduce the enforcement of other crimes. These changes are consistent both with the multitasking of bureaucrats as well as political incentives for re-election, and contribute to our understanding of the nature of crime, politics, and policing during elections.

One in three elected representatives in the lower house of national and state legislatures in India is criminally accused. Using detailed and granular crime data from India, Chapter 3 estimates the impact of politicians with criminal backgrounds on local crime. On one hand, criminal politicians may be elected not despite of, but because of, their ability to control crime and get things done in an environment with weak rule of law. On the other hand, given their criminal backgrounds and political control over local police, criminal politicians may seek to consolidate their rent-seeking interests during their time in office. I use a close election regression discontinuity design and find that having a criminal politician in office lowers weekly counts of serious crimes by 23.6%, even though the total number of complaints remains unchanged. This reduction in crime seems to be partly driven by reduced recording of crime. Further, this chapter suggests that the specific nature of a politician's criminal background matters for outcomes.

Chapter 4 focuses on low participation of women in politics, and explores the impact of gender-specific polling stations on turnout. Using data from Pakistan, which has one of the lowest rates of female voter turnout in the world, we analyse the impact of creating separate-gender polling stations for males and females on voter turnout. The results show that separate gender polling stations reduce turnout for females by 2 percentage points on average, and for males by 1 percentage point on average. The results remain consistent after controlling for the role of resources, norms and mobility-related costs. This paper indicates that the policy of separate-gender polling stations does not alleviate gender-based voting constraints, and may in fact, worsen women's access to voting.

Together, these three papers improve our understanding of crime during elections, criminal governance, and the participation of women in the electoral process, and contribute towards the literature in the fields of economics and political science.

DECLARATION

Chapter 4 of this thesis is co-authored work. It was prepared jointly with Muhammad Khudadad Chattha, who is a former DPhil candidate at BSG. I worked in equal collaboration with Khudadad on every aspect of this paper. Hence, my contribution to this chapter was substantial. All other chapters of this dissertation are my own work.

This thesis consists of approximately 88,392 words - this is calculated using the total number of words on page 2 (348) multiplied by the total number of pages (254). It includes 26 figures and 78 tables.

ACKNOWLEDGEMENTS

The DPhil is at once both a solitary undertaking and one that cannot be completed without the support of a full community. I am lucky to have had many who have helped me to the finish line.

To begin with, I am indebted to my supervisors, Julien Labonne and Martin Williams, for their humbling warmth, kindness, and generosity throughout this journey. I'm grateful to them for putting up with all manner of wild ideas, rabbit holes, and the occasional tears with unbelievable grace and unending confidence in me. Through every nudge and every question, they helped me move forward in the right direction. Martin pushed me to always take a step back, and in doing so, helped me see more clearly. Julien, through his careful reading of each version and every draft, taught me to imbue clarity with conciseness and rigour. If for no other reason, I shall value the DPhil experience for the opportunity to have worked with them.

I'm also deeply grateful to Dapo Akande for his mentorship. Through countless early morning chats, mid-day ice creams, and evening coffees, he has been one of my strongest pillars of support at Oxford. I'm fortunate to have had his wisdom and warmth to turn to throughout this journey.

At the Blavatnik School of Government, I've been lucky enough to find an institutional home to belong to. It has been encouraging and inspiring to watch, work with, and learn from colleagues deeply committed to the idea of a world better led, better served, and better governed. Ruosi and Helen kept the DPhil engine running efficiently and made my life infinitely easier. The investment in the BSG super computer allowed me to conduct my entire data analysis. Philip Leonard at IT always provided prompt troubleshooting guidance on said computer, and Miriam Mendes in the Ethics team made suggestions that greatly improved the design of my qualitative work. From Dean Ngaire's birthday wishes each year, to the kindness of Anne and Anda, who made sure I was looped into life in the department even when I was away, these three years have flown by.

At Exeter College, which has been my home for this time, I am grateful for so much. I was a permanent fixture at Cohen Quadrangle for two years, where the combination of sunshine, coffee, and Maka Papunashvili's geniality contributed in no small measure to my data cleaning efforts. The Fellows' Garden served as refuge in all seasons. I am grateful to the entire college administration, especially Nicola Yeatman, for their help with everyday college and Oxford life. This DPhil would not be possible without the support of the Clarendon Fund and the S.K. Pathak Scholarship, as well as research funds provided by the Centre for the Study of African Economies, Department of Economics, and the Blavatnik School of Government.

In India, I'm incredibly thankful to officials at the National Crime Records Bureau, and in several state police departments, who shared data and helped provide guidance. I'm grateful to the leadership of the Indian Police Foundation for their advice and constant support. My research would not have been possible without all

the interviewees who generously shared their time and experiences with me. These conversations enriched the DPhil process and made it so much more interesting and rewarding. I am also grateful to those who helped me set up the interviews, especially Hemakshi Meghani at the Indian School of Democracy. Finally, I thank Evita Rodrigues, Vanshika Agarwal, and Lavanya Singh, for their assiduous assistance in mapping thousands of police stations to constituency boundaries, and Shreya Murarka for her speedy and valuable help with obtaining data.

This thesis would look very different without the thoughtful comments and suggestions of various faculty, especially Anandi Mani, David Rueda, Nelson Ruiz, Robin Harding, Clare Leaver, Kate Orkin, Pepper Culpepper, Lant Pritchett, Simon Quinn, and Kate Vyborny who took the time to carefully read and comment on individual articles and presentations at various stages. I not only benefitted greatly from, but also enjoyed, the discussions during the Transfer and Confirmation of Status assessments owing to the enthusiastic encouragement and support of Anandi, Nelson, and Robin. I thank Devesh Kapur, Adnan Khan, Ali Cheema, and Arvind Magesan for helpful conversations, and participants of seminars at the Blavatnik School of Government, the Centre for Study of African Economies and the Department of Politics and International Relations at the University of Oxford for their feedback and comments. To all the mentors in institutions past and present who have invested their time, and more importantly, faith, in me, I am truly grateful.

The entire DPhil community at BSG and several friends in Oxford enriched this journey with their presence. I am grateful to them for the discussions, collaborations, memories, and friendship. Ji Baek and Jamie Walsh generously shared their expertise with me. Special thanks are due to Khudadad Chattha for being such a reliable part of the "dream team", for reading through some terrible first drafts, and for encouraging me to celebrate tiny steps as much as large milestones. His companionship made these years all the more fun. The Development Reading Group was an important part of my remote working community, and I am thankful to everyone who was a part of it for their enthusiasm and contributions.

A huge shout-out to the friends in many places who have been there through it all, they know who they are. They have volunteered to track down criminals and politicians, forgiven delayed replies, and kept me going with trips, memes, coffee, and love. A special thanks to the superb Timor-Leste crew in London for everything.

Finally, none of this would have been possible without the love and support of the entire Lakhtakia-Sahai clan, particularly all my grandparents. Living in India for the third year of my DPhil, during the pandemic, reinforced at a personal level the value of governance and the purpose of this journey. It is a journey that began early, as I looked up and tried to emulate the one my dad had. He got me reading and thinking about governance when I was a little girl in a purple tracksuit, and I've never looked back. My brother has been a rock solid partner-in-crime, who literally held my hand as I started scraping data in his New York apartment in the winter of 2019. My mom's immeasurable strength and love has kept me going on the roughest of days, and it has made me who I am. These three have always taught me the importance of giving forward, and yet it is to them that I owe everything.

CONTENTS

1 Introduction **1**

2 Electoral Cycles in Crime: Evidence from India **11**
2.1 Introduction . . . 12
2.2 Theoretical Framework: Crime, Violence and Elections . . . 18
2.3 Institutional Context and Data: Managing and Policing Elections in India . . . 28
2.4 Main Results . . . 39
2.5 Mechanisms: Occurrence vs Enforcement . . . 58
2.6 Role of Bureaucrats' and Politicians' Motivations for Prevention and Enforcement . . . 65
2.7 Conclusion . . . 70

Appendix **80**
2.A Methodology for Qualitative Interviews . . . 80
2.B Additional Observations on Performance Metrics and Transfers . . . 82
2.C Difference-in-Differences Analysis . . . 84
2.D Robustness Checks . . . 90
2.E Sources of Changes in IPC Crimes . . . 105
2.F Heterogeneity within Election Periods: Regression Tables . . . 107
2.G Lists of Acts Included in Analysis . . . 110
2.H Changes in Crimes against Women and SC/STs before an Election . . . 114
2.I Electoral Cycles in Constituencies with Criminal Politicians . . . 116

3 Law Makers or Law Breakers? The Impact of Criminal Politicians on Local Crime **118**
3.1 Introduction . . . 119
3.2 Institutional Context and Data . . . 123
3.3 Empirical Methodology . . . 133
3.4 Reported Reduction in Serious Crime . . . 140
3.5 Differences in Actual or Recorded Crime? . . . 147
3.6 Mechanisms . . . 155
3.7 Conclusion . . . 164

Appendix **171**
3.A Example of a Candidate Affidavit . . . 171
3.B State Summaries . . . 173
3.C Mapping and Police Station Types . . . 175
3.D Datasets . . . 176
3.E RD with Candidate Characteristics that are Discontinuous at Cut-off 178
3.F Results using Optimal rather than Fixed Bandwidth . . . 180
3.G Robustness Tests . . . 186
3.H Tests of RD Validity for Heterogeneity . . . 197
3.I Alternative Mechanisms . . . 201

4 The Gap Within: Impact of Separate-Gender Polling Stations on Voter Turnout **206**

4.1 Introduction . . . 206
4.2 Gender Gap and Creation of Polling Stations . . . 208
4.3 Data . . . 213
4.4 Methodology and Results . . . 214
4.5 Mechanisms . . . 220
4.6 Discussion and Conclusion . . . 223

Appendix **229**
4.A Gender Turnout Gap . . . 229
4.B Voting Process . . . 230
4.C Index Definitions and Descriptions . . . 232
4.D Data . . . 235
4.E Polling Station Descriptives . . . 236

5 Conclusion **237**

LIST OF FIGURES

2.1 Stylized Model of Timing . . . 22
2.2 Sub-Period Trends in Case, Violation, and Non-Penal Counts are Consistent with Overall Trends, even though Pre- and Post-Poll Trends Differ 56
2.3 Most Changes in Crime and Serious Crime come during and after Polling 57
2.C.1 Parallel Trends Hold for States of Andhra Pradesh and Telangana . . . 85
2.D.2 Robustness of Results on Murder to the Exclusion of States from the Analysis . . . 97
2.D.3 Effects Taper Off in Moving Away from the Election Period. . . . 104
2.E.4 Coefficient of Election Period by IPC Chapter . . . 105
3.1 Electoral Races are, On Average, Quite Competitive . . . 132
3.2 The Running Variable, Margin, is Continuous at the Cut-off . . . 137
3.3 The Assignment Variable, Criminal, is Discontinuous at the Cut-off . . . 137
3.4 There is No Evidence of Sorting of Winners (McCrary, 2008) . . . 140
3.5 There is No Evidence of Sorting of Winners (Cattaneo, Jansson and Ma, 2020) . . . 141
3.6 Positive Relationship between Crime and Criminal Vote Share . . . 142
3.A.1 Sample Affidavit . . . 171
3.A.2 Sample Affidavit of a Candidate with Details of Crime Charges . . . 172
3.G.3 Results are Robust at Alternative RD Bandwidths . . . 190
3.G.4 Placebo Tests with Alternative Cut-off Points . . . 191
3.G.5 Results Remain Robust to Exclusion of Individual States . . . 191
3.G.6 Time Heterogeneity of RD Coefficient . . . 196
3.H.7 McCrary Test for Sorting with Alternative Criminality Definitions by Politician Type . . . 200
4.1 Pakistan has a Large Difference between Female and Male Turnout . . . 209
4.2 Gender Gap in Turnout in Pakistan . . . 210
4.3 Voting Process in the 2018 General Election . . . 213
4.4 Illustration of Main Empirical Specifications . . . 215
4.5 Combined Polling Stations Have Higher Turnout than Separate-Gender Ones . . . 216
4.A.1 Males are More Likely to Vote in National Elections than Females . . . 229

LIST OF TABLES

2.1 Hypotheses . . . 27
2.2 Sub-Periods within the Election period and Duration . . . 34
2.3 Summary of Hypotheses, Measurement, and Empirical Results . . . 37
2.4 Impact of Election Periods on Main Outcome Variables in Full Dataset . . . 42
2.5 Impact of Election Periods on Daily Count of Order-related Violations . . . 44
2.6 Impact of Election Periods on Daily ACLED Count and Fatalities . . . 46
2.7 Impact of Election Periods on Daily Count of Violations related to Alcohol and Gambling . . . 47
2.8 Impact of Election Periods on Daily Counts of Body and Property Crime . . . 49
2.9 Impact of Election Periods on Daily Murders . . . 50
2.10 Impact of Election Periods on Daily Count of Crimes against Women, Children, SC/STs . . . 53
2.11 Impact of Election Periods on Daily Count of Preventive Activity . . . 54
2.12 Alternative Mechanisms . . . 68
2.C.1 DiD: Impact of Election Periods on Daily Crime in Full Dataset . . . 87
2.C.2 DiD: Impact of Election Periods on Daily Preventive Activity . . . 88
2.C.3 DiD: Impact of State Election Periods on Daily Murder Count . . . 89
2.D.4 Impact of Election Periods on Daily Crime in the Partial Dataset . . . 91
2.D.5 DiD: Impact of Election Periods on Daily Crime in the Partial Dataset . . . 92
2.D.6 Impact of Election Periods on Daily Crime using By-Elections . . . 94
2.D.7 Impact of Election Periods on Daily Crime using By-Elections II . . . 96
2.D.8 Impact of Election Periods on Daily ACLED Count and Fatalities excluding Jammu & Kashmir . . . 98
2.D.9 Impact of National Election Periods on Daily Crime . . . 100
2.D.10 Impact of Election Periods on Average Weekly Crime . . . 101
2.D.11 Impact of Election Periods on Daily Crime in Partial Dataset using Alternative Clustering . . . 102
2.F.12 Impact of Election Sub-Periods on Daily Crime in Full Dataset . . . 108
2.F.13 Impact of Election Sub-Periods on Daily Crime in Partial Dataset . . . 109
2.H.14 Impact of 60-day Prior to Election Period on Daily Crimes Against Women, SC/STs . . . 115
2.I.15 Impact of Election Periods on Daily Crime in Constituencies with Criminal Politicians . . . 117
3.1 Summary Statistics of Crime at the Week-Police Station Level . . . 129
3.2 Summary Statistics of Crime Counts by Criminal Politicians . . . 131
3.3 Constituency Characteristics are Smooth at the Cut-off . . . 138
3.4 Candidate Characteristics are Smooth at the Cut-off . . . 139
3.5 Impact of Criminal Politician on Weekly Serious Crime . . . 143
3.6 Impact of Criminal Politician on Weekly Crime Outcomes . . . 144
3.7 Regression Discontinuity Estimates by IPC Chapter . . . 146
3.8 Impact of Criminal Politician on Weekly Murder . . . 148
3.9 Distribution of ACLED Data, 2016-2019 . . . 149
3.10 Impact on Political Violence . . . 151
3.11 Relationship between Criminal Constituency and Domestic Violence . . . 153
3.12 Impact of Criminal Politicians on Weekly Domestic Violence . . . 153
3.13 Association between Crime Victimization . . . 154
3.14 Most Common IPC Crimes Committed by Politicians . . . 157
3.15 Impact of Criminal Politician by Type on Weekly Serious Crime . . . 158
3.16 Impact of Criminal Politician by Type on Weekly Murder . . . 159
3.17 Impact of Criminal Politician by Type on Weekly IPC Chapter Count . . . 160
3.18 Impact of Criminal Politician's Own Crime on Weekly IPC Chapter Count . . . 162
3.B.1 Summary of States, 2008-2019 . . . 173
3.B.2 Summary of States and UTs Not Included . . . 174
3.C.3 Distribution of Police Station Type . . . 175
3.C.4 Summary of Crime Count at the PS-Day Level by Police Station Type . . . 175
3.D.5 Datasets Used in the Main Analysis . . . 176

3.E.6 Impact of Literate Politician on Weekly Crime Outcomes . . . 178
3.E.7 Impact of Graduate/Professional Politician on Weekly Crime Outcomes . . . 179
3.E.8 Impact of Regional Party Politician on Weekly Crime Outcomes . . . 179
3.F.9 Impact of Criminal Politician on Weekly Crime Outcomes over Optimal Bandwidth . . . 180
3.F.10 Regression Discontinuity Estimates by IPC Chapter over Optimal Bandwidth 181
3.F.11 Impact of Criminal Politician on Weekly Count of Murder over Optimal Bandwidth . . . 182
3.F.12 Impact on Political Violence over Optimal Bandwidth . . . 183
3.F.13 Impact of Criminal Politicians on Weekly Domestic Violence over Optimal Bandwidth . . . 183
3.F.14 Impact of Criminal Politician by Type on Weekly Serious Crime over Optimal Bandwidth . . . 184
3.F.15 Impact of Criminal Politician by Type on Weekly Murder over Optimal Bandwidth . . . 185
3.G.16 Impact of Criminal Politician on Weekly Serious Crime using Alternative Specifications . . . 187
3.G.17 Impact of Criminal Politician on Weekly Serious Crime using Alternative Kernel Functions . . . 188
3.G.18 Impact of Criminal Politician on Weekly Serious Crime using Alternative Clustering . . . 189
3.G.19 Results Remain Robust after Excluding States with Low Data Availability . . . 192
3.G.20 Impact of Criminal Politician on Weekly Serious Crime Excluding Outliers . . . 193
3.G.21 Results are not driven by Timing . . . 195
3.H.22 Smoothness of Constituency Characteristics at Cut-off by Politician Type . . . 198
3.H.23 Smoothness of Candidate Characteristics at Cut-off by Politician Type . . . 199
3.I.24 Connections: Impact of Having Criminal Chief Minister . . . 203
3.I.25 Impact of Having Criminal Politician at the National Level . . . 204
4.1 Distribution of Polling Locations with Different Polling Station . . . 211
4.2 Distribution of Polling Station Types . . . 211
4.3 Lower Turnout in Separate-Gender Polling Stations . . . 218
4.4 Summary of Indices Used for Analysis . . . 222
4.5 Results are Consistent after Including Role of Resources, Norms, Voting Together 224
4.D.1 Data Sources Used for Analysis . . . 235
4.E.2 Distribution of Polling Stations by Polling Location . . . 236
4.E.3 Share of Different Types of Polling Stations by Province . . . 236

CHAPTER 1

Introduction

Background and Motivation

One of the key functions of the state, which is widely understood to have a monopoly over violence (Weber, 1965), is to provide security for citizens. In this thesis, I examine questions of political economy and governance through the lens of crime, politics, and policing, in particular, looking at how the incentives of government officials (politicians and bureaucrats) affect the nature and magnitude of crime. I study the relationship between crime and politics in two specific contexts – one, at the time of elections (Chapter 2), and two – when a criminal politician is closely elected into office (Chapter 3). In both chapters, I study how politicians' re-election incentives run up against their incentives for rent-seeking, and highlight the importance of incentives for politicians' and police behaviour. In Chapter 4, I study the impact of a policy aimed at increasing female political participation on voter turnout in Pakistan, and find evidence for unintended consequences of the policy.

I answer these questions in three original, standalone articles, using a combination of large-scale administrative data, media-reported micro-data, and qualitative data from interviews. This thesis focuses on South Asia, in particular, on India and Pakistan.

In general, there are two features of crime and policing that are especially worth noting. First, policing on the frontlines is, by its very nature, transactions-intensive and discretionary (Wilson, 1978). The day-to-day activities of crime prevention, administration, and investigation – whether it is issuing a verbal warning, deciding

to register a victim's complaint, or giving a speeding vehicle a ticket – involve dispersed officials making decisions about when to take action or enforce the law. Similarly, the decision to respond to large-scale events such as riots often depends on judgment of the actors involved. Second, the nature of policing, unlike several other forms of service delivery involves the 'imposition of obligations' (Andrews et al., 2017), rather than the provision of public goods and services. Combined with the discretionary nature of policing, this renders policing particularly vulnerable to agency problems related to enforcement, in particular influence and corruption (Becker and Stigler, 1974).

As a result, the relationship between politicians and bureaucrats, increasingly studied in a large empirical literature (Iyer and Mani, 2012; Gulzar and Pasquale, 2017; Brierley, 2020), can be particularly important to study in the case of policing, especially in contexts where politics often relies on the use of raw muscle power. Violence, in this setting, can be used to both contest and win elections, as well as govern once in office (Vaishnav, 2017). This suggests that political incentives can affect crime and policing in several ways.

For example, politicians could improve performance on crime to enhance voter welfare or to signal effectiveness to voters. They could employ the brute force of the police to coerce, influence, or to protect. They might use violence to consolidate gains from crime. They may increase security and safety of citizens, or protect themselves and their associates from prosecution. Yet, political control over the police can also be leveraged in positive ways, as when the election of female representatives leads to an improvement in the recording of crimes against women by the police (Iyer et al., 2012). However, it can also be used in more pernicious ways. Research has shown that the discretionary decision of the police to control riots, once they have broken out, depends on political incentives (Brass, 2003; Wilkinson, 2004). In fact, political control of the police is understood as contributing to the decline in the rule of law (Bayley, 1983). This thesis studies the manner in which

political and bureaucratic incentives affect crime.

In Chapter 2 of this thesis, I examine how political incentives to appear competent and reduce crime prior to elections run up against political incentives to use violence as an electoral strategy to influence voters, both in a bid to win elections. Subsequently, in Chapter 3, I study how incentives of politicians who are criminally accused affect the nature and magnitude of local crime, distinguishing between those who use crime to signal their effectiveness in a context with low state capacity and weak rule of law, and those who use crime in pursuit of rent-seeking interests based on their serious criminal background. Finally, in Chapter 4 of this thesis, I study the impact of a specific policy that encourages the political participation of female voters on actual turnout of female as well as male voters.

In terms of structure, this is an article-based thesis, comprising of three original, standalone articles. The Introduction (Chapter 1) provides the background and motivation for the thesis, a summary of the main findings and contributions of each of the articles. At the end, the Conclusion (Chapter 5) summarizes the thesis, discusses policy implications that emerge, and suggests future avenues for research in this context.

Main Results

This article-based thesis aims to study the political economy of crime in developing countries, particularly the role of crime during elections, criminal governance, as well as women's participation in the electoral process. To study these questions, I obtain what is possibly the most detailed and granular dataset on crime in India, containing the universe of all crimes registered over the 2008-2019 period. I also work with police departments in the country to map individual police stations to constituencies for the first time, and scrape online data on politicians' criminal records. I combine this with data from third-party media sources, surveys, as well

as data on constituency characteristics. I primarily use econometric methods of rigorous causal inference including regression discontinuity design, fixed effects as well as difference-in-differences models. I also draw on insights from semi-structured qualitative interviews. The three articles in this thesis contribute to the fields of economics and political science, and are described below.[1]

In Chapter 2, I study electoral cycles in crime in India. The literature on electoral cycles suggests that politicians improve performance in the run up to elections in order to appear more competent, which would imply a decrease in crime prior to elections. On the other hand, the vast literature on political violence suggests that, in many countries, electoral violence is strategically used by politicians to influence voters and win elections, suggesting that violence may increase before elections. This article studies the impact of election timing on crime and the nature of law enforcement using large-scale administrative data from India. I undertake fixed effects and difference-in-differences analyses, and provide some of the most detailed and rigorous evidence for the existence of electoral cycles in crime. I use rich variation in type of crime as well as within election period timing (for example, comparing pre-poll and post-poll periods within the official election period) across multiple states in India.

I show that there is a mixed impact of upcoming elections on local crime. While crime against public order increases, crimes against individuals decrease. I present a theoretical framework that examines the role of crime prevention and law enforcement by the police. Consistent with the predictions from the framework, I show that there is a change in the nature of law enforcement during this time, as police increase preventive activity when elections approach. Data from semi-structured interviews with elite policymakers and frontline officials in India suggests that enforcement behaviour changes as well, with an increase in enforcement of crimes related to public order, and a decrease in the enforcement of all other crimes. These changes in

[1] I use the terms 'chapter', 'article', and 'paper' interchangeably.

prevention and enforcement are consistent with multitasking by bureaucrats as well as the re-election incentives of politicians. These findings contribute to our understanding of the nature of crime, politics, and policing during elections in developing countries.

In Chapter 3, I focus on the relationship between criminally accused politicians and the nature of local crime. One in every three elected representatives in the lower house of the Indian Parliament and in state Legislative Assemblies is criminally accused. With their control over local criminals and the local police, criminal politicians have the ability to potentially impact local crime. Using some of the most detailed and granular data on crime in India, this paper estimates the impact of electing politicians with criminal backgrounds on local crime. On one hand, this speaks to a theory where criminal politicians are elected not despite of, but because of, their ability to control crime and get things done in an environment with weak rule of law. On the other hand, given their criminal backgrounds and political control over local police, criminal politicians may seek to consolidate their rent-seeking interests during their time in office. Using a close election regression discontinuity design, I find that having a criminal politician in office lowers weekly counts of serious crimes by 23.6%, even though the total number of complaints filed remains unchanged. I document and explore these effects empirically in the paper.

To further understand the role of signalling and rent-seeking motives, I look at different 'types' of criminals in close election races – distinguishing between those who are accused of serious crimes, such as murder and rape, from those accused of 'non-serious' crime, such as unlawful assembly. I find that the kind of criminal profile that politicians have matters - 'non-serious' criminals reduce crimes against body, property, public tranquillity, and offences of defamation and criminal intimidation. On the other hand, serious criminal politicians reduce crimes against public servants, and against religion, but have no impact on crimes against the body or property. Finally, I find that politicians' own criminal profile matters - for example, being

accused of crimes against property or religion affects the incidence of those very kinds of crimes differently compared to other criminal politicians who are not accused of that crime. These findings contribute to our understanding of the impact of criminality in politics on the incidence of crime.

Chapter 4 focuses on low participation of women in politics, and explores the impact of gender-specific polling stations on turnout. Governments in several developing countries, including Afghanistan, Algeria, Argentina, Chile, Ecuador, Egypt, Jordan, Kuwait, Lebanon, Mozambique, Pakistan, Sri Lanka, and Zanzibar, are increasingly adopting the use of female-friendly facilities such as the use of separate voter registration centres, women-only polling stations, and priority queues for women (UN Women and United Nations Development Programme, 2015; Electoral Knowledge Network, 2013). Yet, we know very little about the effectiveness of such policies.

Using data from Pakistan, which has one of the lowest rates of female voter turnout in the world, we analyse the impact of creating separate-gender polling stations for males and females on voter turnout. We compare the turnout of female voters in female-only polling stations with the turnout of female voters in combined polling stations within close geographic localities in the 2018 general election. Similarly, we compare male voter turnout in male-only and combined polling stations. We find that being assigned to separate-gender polling stations is associated with a reduction in turnout for both women and men by 2 and 1 percentage points respectively, when compared to the turnout of women and men in mixed-gender polling stations. Our results remain consistent after controlling for the role of resources, norms and mobility- related costs. These results indicate that separate-gender polling stations do not alleviate gender-based voting constraints faced by women.

Contributions

Together, these papers contribute to our understanding of crime and politics, and to the literature on policing, politics, and crime in economics and political science. The current literature on the economics of crime and optimal policing is almost entirely based in developed countries, in particular in the US. Through the lens of crime and politics, I look at questions related to agency behaviour in governance – looking at how politicians and bureaucrats affect crime in the context of a developing country with weak rule of law and competitive elections that are prone to violence.

Chapter 2 contributes to the literature on elections and crime by providing some of the most detailed and rigorous evidence on the existence of electoral cycles in crime. Second, this article highlights the choice of the police to prevent crime in addition to their enforcement of the law in the theoretical framework, and provides some of the earliest evidence of electoral cycles induced by bureaucratic behaviour (prevention and enforcement). In this way, I contribute to the literature on electoral violence, where the focus is on the role of law enforcement agencies as perpetrators of state repression or victims of insurgent violence (Daxecker, 2020) rather than as agents seeking to prevent and control the occurrence of violence. Finally, this paper also contributes to the literature on optimal policing and the literature examining the strategic behaviour of the police in developing country contexts (Prendergast, 2001; Banerjee et al., 2021; Banerjee et al., 2019; Ahmed et al., 2021).

Chapter 3 contributes to our understanding of crime and politics in a context where politicians routinely have criminal records and face criminal charges, including serious ones such as murder. This is one of the first papers to directly study the impact of criminal politicians on crime outcomes. Further, since politicians in this context do routinely run up against the law, for example, by protesting, this paper makes a contribution by presenting the heterogeneity in the outcomes where politicians are accused of serious crimes as compared to non-serious crimes. This can help us better

understand rent-seeking and signalling behaviour by political candidates. Finally, this paper also contributes to the literature studying the impact of politics on the recording of crime, and suggests that recording of crimes by the police may differ in constituencies where criminals are elected.

This work on crime and politics makes two important contributions. First, it adds to the nascent literature on optimal policing in developing countries. Most of the economics literature on crime focuses on developed countries, in particular, the US, which is quite different from the policing context in developing countries.[2] A lot less is known about the relationship between crime and politics in the South Asian context. On the empirical side, one important challenge in studying crime is the difficulty in distinguishing between actual, reported, and recorded crime. Previous work has shown that not all crime is recorded (Wilson, 1978). The papers in this thesis use administrative crime data combined with additional media-reported and survey data. Using multiple sources of data helps overcome some of the challenges associated with the mis-classification, mis-measurement, and incompleteness of crime and violence data in the study of policing and politics.

Finally, Chapter 4 contributes to our understanding of turnout, and provides some of the earliest evidence on the impact of separate-gender polling stations on the turnout of female and male voters. In doing so, it contributes to the literature on turnout and the political participation of women in developing countries.

[2] We also have a better understanding of the relationship between crime and politics in countries in South America.

References

Ahmed, Hamna, Dareen Latif, and Kate Vyborny, "The Unintended Consequences of Political Accountability: Quasi-experimental Evidence from Policing in Pakistan," November 2021.

Andrews, Matt, Lant Pritchett, and Michael J. V. Woolcock, *Building State Capability: Evidence, Analysis, Action*, New York: Oxford University Press, 2017.

Banerjee, Abhijit, Esther Duflo, Daniel Keniston, and Nina Singh, "The Efficient Deployment of Police Resources: Theory and New Evidence from a Randomized Drunk Driving Crackdown in India," *National Bureau of Economic Research Working Paper 26224*, September 2019.

_ , Raghabendra Chattopadhyay, Esther Duflo, Daniel Keniston, and Nina Singh, "Improving Police Performance in Rajasthan, India: Experimental Evidence on Incentives, Managerial Autonomy, and Training," *American Economic Journal: Economic Policy*, February 2021, *13* (1), 36–66.

Bayley, David H., "The Police and Political Order in India," *Asian Survey*, 1983, *23* (4), 484–496. Publisher: University of California Press.

Becker, Gary S. and George J. Stigler, "Law Enforcement, Malfeasance, and Compensation of Enforcers," *The Journal of Legal Studies*, 1974, *3* (1), 1–18.

Brass, Paul R., *The Production of Hindu-Muslim Violence in Contemporary India*, New Delhi ; Oxford: Oxford University Press, 2003.

Brierley, Sarah, "Unprincipled Principals: Co-opted Bureaucrats and Corruption in Ghana," *American Journal of Political Science*, 2020, *64* (2), 209–222.

Daxecker, Ursula, "Unequal votes, unequal violence: Malapportionment and election violence in India," *Journal of Peace Research*, January 2020, *57* (1), 156–170.

Electoral Knowledge Network, "Systems with Separate Polling Stations for Men and Women," 2013.

Gulzar, Saad and Benjamin J. Pasquale, "Politicians, Bureaucrats, and Development: Evidence from India," *American Political Science Review*, February 2017, *111* (1), 162–183.

Iyer, Lakshmi, Anandi Mani, Prachi Mishra, and Petia Topalova, "The Power of Political Voice: Women's Political Representation and Crime in India," *American Economic Journal: Applied Economics*, October 2012, *4* (4), 165–193.

_ and _ , "Traveling Agents: Political Change and Bureaucratic Turnover in India," *Review of Economics and Statistics*, 2012.

Prendergast, Canice, "Selection and Oversight in the Public Sector, With the Los Angeles Police Department as an Example," *National Bureau of Economic Research Working Paper 8664*, December 2001.

UN Women and United Nations Development Programme, "Inclusive Electoral Processes: A Guide for Electoral Management Bodies on Promoting Gender Equality and Women's Participation," Technical Report 2015.

Vaishnav, Milan, *When Crime Pays: Money and Muscle in Indian Politics*, New Haven: Yale University Press, 2017.

Weber, Max, *Politics as a Vocation* number 3. In 'Facet books. Social Ethics Series.', Philadelphia: Fortress Press, 1965.

Wilkinson, Steven, *Votes and Violence: Electoral Competition and Ethnic Riots in India* Cambridge Studies in Comparative Politics, Cambridge: Cambridge University Press, 2004.

Wilson, James Q., *Varieties of Police Behavior: The Management of Law and Order in Eight Communities*, Cambridge, MA: Harvard University Press, 1978.

CHAPTER 2

Electoral Cycles in Crime: Evidence from India

Abstract

Our understanding of the role of formal and informal institutions in determining electoral violence is restricted to mostly political institutions. Much less is known about the role of administrative factors, in particular the role of law enforcement, in anticipating, deterring, or controlling violence at the time of elections. This paper studies the impact of election timing on crime and the nature of law enforcement in a developing country known for electoral violence. Using administrative crime data from India in the 2008-2019 period, I undertake fixed effects and difference-in-differences analyses, and provide detailed and rigorous causal evidence for change in the nature of crime and the composition of policing effort as elections approach. I show that upcoming elections have a mixed impact on crime – increasing crimes against public order while reducing crimes against individuals, such as those related to bodily offences, property, or women. I suggest that these cycles are driven by changes in police behaviour – as elections approach, the police sharply increase preventive activity and the enforcement of crimes related to public order, and reduce the enforcement of other crimes. These changes are consistent both with the multitasking of bureaucrats as well as political incentives for re-election. Together, these results contribute to our understanding of the nature of crime, politics, and policing during elections in developing countries.

2.1 Introduction

Electoral cycles are caused by politicians' incentives to appear competent by making policy choices in the pre-electoral period that they may not make at other times, or once elected into office. However, unlike other economic variables, in the case of crime, politicians' deployment of violence as an electoral strategy, long studied in the literature on electoral violence, runs up against their incentives to improve service delivery and project competent performance by reducing crime. How do bureaucrats in charge of election security anticipate and respond to these changes in violence and political incentives, and how does their strategic decision-making affect patterns of crime, crime prevention, and law enforcement?

In this paper, I study how election timing affects crime – crimes against public order (such as riots), and crimes against private individuals (homicides, theft, crimes against women) – focusing on the pre-election period. I ask whether security agencies that are responsible for policing crime and maintaining law and order are able to anticipate a change in the nature of crime in the run-up to elections. In a setting where the same agency is responsible for election security as well as day-to-day crime administration, I examine the incentives and conditions under which the police optimally choose to prevent crime or enforce the law. Finally, I examine the role of political and bureaucratic incentives for changes in prevention and enforcement.

To answer these questions, I look at the impact of elections on the magnitude and composition of crime in a developing country with weak rule of law and a robust electoral system. I hypothesize that a change in the nature of crime can be anticipated by agencies responsible for election security, who take steps to prevent violence under certain conditions. I identify specific actions that can be understood as having a preventive nature, and adapt the canonical model of crime from Donohue & Levitt (2001) by incorporating the prevention decision of the police as distinct from their enforcement decision. Whereas enforcement is the choice of the police to

respond to a crime once it has occurred, by registering a complaint, undertaking an investigation, and making arrests, preventive activity in the form of, say, patrolling, must take place before a crime has even been committed. I argue that the changes in the nature and magnitude of crimes that we observe are driven by the trade-offs between enforcement and prevention that the police face in a context where they are responsible for both election security and day-to-day crime administration. This is consistent with the optimization of multitasking bureaucrats, as well as political incentives for re-election, which might entail improved performance on crime (lower individual crimes) *as well as* greater use of political violence to win elections (higher crimes against public order).[3]

Using administrative data on daily crime from 14,970 police stations in India in the 2008-2019 period, I am able to identify the impacts of an upcoming election on crime. With over 50 million observations, and including information on the universe of all crimes, from homicides to drunk driving, this dataset represents some of the most granular and fine-grained data on crime used in this context. I combine this crime data with detailed information on the schedule of the elections from notifications published by the Election Commission (EC) of India. Using variation in the type of crimes committed as well as in the timing of elections – across states as well as across sub-periods within an election – to undertake fixed effects and difference-in-differences analyses, I provide causal evidence for change in the nature of crime and composition of policing effort as elections approach. I also use data from qualitative interviews that I conducted with senior as well as frontline officials from the police, the Election Commission, and political representatives, in addition to third-party reported violence data from the Armed Conflict Location and Event Data Project (ACLED) to examine the role of various mechanisms and heterogeneities.

My results show that elections have a mixed impact on crime. There is an overall

[3]Qualitative interviews with the police suggest that increased preventive activity is driven by the role of the Election Commission, but I cannot rule out the possibility that prevention may be driven by political incentives and control over the police.

increase in the number of cases registered during the election period. This increase is driven, to a large extent, by an increase in preventive cases filed against criminals by the police, showing that the police is able to anticipate changes in crime and respond to them. As we would further expect, electoral offences, such as 'illegal payments in connection with an election' increase during this period. There is also an increase in crimes against public order, such as an increase in the cases of rioting or destruction of public property, consistent with the very political nature of these crimes and the focus of the police on order-related crimes under the guidance of the Election Commission. However, there is a sharp decline in crimes against individuals, including cases related to bodily and property offences. Crimes against women and children also decline. These findings represent some of the most detailed evidence of change in the nature and magnitude of crime in a developing country in the run-up to an election.

My theoretical framework suggests that the net impact on crime observed is the outcome of changes in both criminal and police behaviour – including prevention and enforcement activities – over the election period. I use qualitative interviews to disentangle the role of changes in prevention and enforcement behaviour. Evidence from these interviews indicates that the increase in preventive activity is accompanied by an increase in enforcement of crimes related to public order, and a decrease in enforcement of other crimes. "It is possible that because there is so much crime already due to elections, some of the more routine or regular cases are not registered or given so much importance," said one police officer. (P51) Qualitative evidence suggests that the police have a choice between prevention and enforcement, and their behaviour in the presence of this trade-off generates the crime cycles that we observe. To what extent a change in the incidence of crime reflects a change in its occurrence as opposed to a change in its enforcement depends on the nature of the crime itself.

These changes in police behaviour are consistent with bureaucratic incentives as well

political incentives. One one hand, bureaucrats are under the control of the independent Election Commission, which is solely in-charge of the conduct of elections at the national and state levels and controls the local administration and the police, including their transfers, during the election period. The monitoring and supervision of the police by the EC may be associated with an increase in preventive activity and the enforcement of laws related to public order. However, the EC has very little to say about the conduct of day-to-day crime administration. Qualitative evidence suggests that this plays a role in reducing the enforcement of other crime. This optimization by the police in the face of multiple tasks and EC monitoring is consistent with the behaviour we would expect from multitasking bureaucrats. On the other hand, politicians and bureaucrats may also be driven by political incentives for re-election, whereby despite not having formal control during this time, politicians are able to encourage the police to undertake more preventive action, which could both reduce individual crime and be targeted towards political opponents, while at the same time allowing certain kinds of political violence with electoral benefits (say, in the form of riots) to take place. This possibility cannot by itself explain the rise in enforcement of public order offences (such as the increase in traffic violations), but without further information on the targeting of preventive behaviour and its impact on political outcomes, I cannot fully rule out this possibility.

I make three main contributions in this paper. First, I provide some of the most detailed and rigorous evidence of the existence of electoral cycles in crime, and some of the earliest evidence of electoral cycles induced by bureaucratic behaviour (prevention and enforcement). The existence of electoral cycles in developing countries has been shown for several economic outcomes, including taxation and public spending (Khemani, 2004), employment (Labonne, 2016), food prices (Dar et al., 2018), and public hiring (Pierskalla and Sacks, 2019). There is much less information on electoral cycles in crime, with the exception of Ghosh (2006) and Meloni (2018), who look at a very limited set of outcomes using aggregated annual data from In-

dia and Argentina, respectively.[4] This paper expands the type of crime studied far beyond homicides and thefts to include traffic violations, destruction of public property, incidents relating to alcohol and gambling, crimes against women, children, etc. Further, using detailed election notifications data, I am able to compare not just the election period with the non-election period, but also examine changes *within* the election period. The trends within these sub-periods, for example, right before and after the polling date, further help us understand changes in policing behaviour during election time.

Second, I contribute to the literature examining the strategic behaviour of the police (Prendergast, 2001; Banerjee et al., 2021; Banerjee et al., 2019). I highlight the choice of the police to prevent crime in addition to their enforcement of the law.[5] I show that preventive activity by the police increases during the election period, and qualitative evidence suggests that the enforcement of other crimes decreases. In doing so, I contribute to the literature on electoral violence, where the focus is on the role of law enforcement agencies as perpetrators of state repression or victims of insurgent violence (Wilkinson, 2004; Daxecker, 2020) rather than as agents seeking to prevent and control the occurrence of violence.[6] This is consistent, among other explanations, with the optimal behaviour of public-sector agents operating in an environment with multiple objectives (Holmstrom & Milgrom, 1991), under institutional incentives created by the Election Commission. In a context where the same law enforcement agency is responsible for both election security and day-to-day crime administration, this paper highlights the importance of taking a more unified view of election and non-election related crime, in line with other recommen-

[4]However, Levitt (1997), Di Tella and Schargrodsky (2004) and Draca et al. (2011) use the electoral cycles in police hiring to causally estimate the impact of policing on crime. Berdejó and Yuchtman (2013) show that serious crimes are sentenced more severely at the end of a judicial electoral cycle, as a response to political pressure.

[5]Chalfin and McCrary (2017) review the literature on the economics and criminology of deterrence, which focuses on how potential criminals respond to the threat of deterrence, as measured by the certainty and severity of the punishment. The empirical evidence in this literature is almost entirely drawn from the work on policing and criminal justice policy in the United States.

[6]Little academic research currently exists on the effectiveness of different types of election violence prevention strategies (Taylor, 2018).

dations made by Staniland (2014). This change in behaviour may also be consistent with bureaucratic and political collaboration in line with political incentives for re-election.

Finally, by using both administrative crime data and media-reported political violence data at the daily, sub-national level, this paper overcomes several challenges associated with the mis-classification, mis-measurement, and incompleteness of crime and violence data in the study of elections. Both administrative crime data and media-reported data on political violence are not perfect and have systematic biases. For example, government collected administrative data tends to exclude deaths that might be related to battles, insurgencies, civil wars, etc. It also excludes crimes that are not reported to the police. On the other hand, media-reported violence data excludes any incident that is not 'political' or 'electoral' – but what is 'electoral' is difficult to identify, classify, and code consistently even in the best of datasets (Staniland, 2014). This data also excludes other incidents of violence, such as domestic violence, other instances of electoral crime that are less visible or unlikely to be reported in the media, for example, intimidation of voters, or non-violent electoral offences, such as vote-buying. Since triangulation is most useful when multiple data sources exist and do not suffer from the same biases, the use of both administrative crime data and detailed political violence event data presents an advantage (Hendrix and Salehyan 2015; Weidmann, 2016; von Borzyskowski and Wahman, 2021). I am able to include the battles and insurgencies that are excluded by administrative data, non-political violence that is excluded by the Armed Conflict Location and Event Data Project (Raleigh et al., 2010), and political violence that is not reported in the media, for which a police complaint is filed.[7] Since both sets of data are at the daily level, I am able to overcome the challenges that arise with looking at crime at an annual, aggregated level. Finally, the data used in this paper contributes to our understanding of the local and temporal patterns of violence and crime. Given the

[7]However, I analyse the two datasets separately and never combine or aggregate them. Information on crimes unreported by both victims and the media is not captured by this paper.

shortcomings of sub-national media-reported data, not a lot is known about local causes of conflict, such as disagreements over land, that are often politicized during elections and lead to electoral violence.[8] This paper can help us examine the local issues reported in an average police station, on an average day during the election period, contributing to our understanding of what electoral violence looks like away from the centres of national political activity.

The rest of the paper is structured as follows. Section 2.2 lays out the theoretical framework. Section 2.3 provides greater information about the management and policing of elections in India, and summarizes the sources of data used in the study. Section 2.4 describes the empirical strategy and the main results. Sections 2.5 and 2.6 discuss the various mechanisms at play, including the role of enforcement and incentives, respectively, using data from qualitative interviews. Section 2.7 concludes with a discussion about what we can learn from this research and suggests future avenues for work.

2.2 Theoretical Framework: Crime, Violence and Elections

What is the impact of upcoming elections on crime? On one hand, a limited empirical literature studies the electoral cycle in crime, driven by political incentives to reduce crime before elections, and finds that homicide and property crimes *decline* at the time of elections. Using annual data, Ghosh (2006) finds a significant decline in the incidence of theft but not of homicides during election years in India. Meloni (2018) finds a V-shaped cycle in crime, with a sharp decrease in the total crime rate and the incidence of property crimes in Argentina during gubernatorial election years, and an upwards jump in the post-election year. He also finds a significant decrease in homicides during the election year but no change in the subsequent year.

[8]Staniland (2014) points out that local dynamics, conflicts, and cleavages, which are used by local actors to generate political violence, can be distinct from national political cleavages.

On the other hand, a rich literature on electoral violence finds a *spike* in the number of violent incidents at the time of elections, motivated by the strategic use of violence by political elites (Harish and Little, 2017; Birch et al., 2020; Hafner-Burton et al., 2018). For example, Wilkinson (2004), in his work on communal riots in India, emphasizes the use of violence as an electoral strategy in the face of ethnic divisions.

To study the impact of upcoming elections, I focus on two broad outcome categories of crime – crimes against public order, and crimes against individuals.[9] Incidents such as homicide, theft, or rape affect individual victims who are few in number in a typical incident. On the other hand, crimes against public order, such as riots, are events that typically involve and affect a larger number of people, or affect 'order' in a visible way (for example, unlawful assembly restrictions that may apply to non-violent protests).[10] In this paper, I analyse the impact of elections on over 150 laws, in addition to the 511 sections of the Indian Penal Code, by focusing on these broad categories of crimes against public order and crimes against private individuals.

Furthermore, in both the literatures on electoral cycles in crime and on political violence before elections, the relevant mechanisms are dependent on the behaviour of politicians, and do not consider the role of local security agencies in anticipating or preventing election-related violence. The theoretical framework outlined in this section focuses on the role of the police in preventing crime and enforcing the law. At all times, but especially during elections, the police have an additional tool to maintain law and order – in addition to enforcing the law after an infraction occurs, they can also prevent crime before it has even taken place, for example, by increasing patrolling.

This section presents a framework that can help us think about the impact of upcoming elections on various kinds of violence and crime, and the mechanisms through

[9] I thank Anandi Mani and Devesh Kapur for encouraging me to make this distinction.

[10] Election-related violence could encompass both kinds of instances – the murder of a political rival (individual), or an electorally-motivated instance of group violence (between members of rival political or ethnic groups, for example).

which this effect operates. I proceed in three steps. I first adapt an existing model of crime from Donohue & Levitt (2001) to expand the range of tools available for law enforcement at the time of elections – including not just enforcement, but also prevention, decisions. Then, I use this model to make predictions about the impact of election timing on crimes against public order and private individuals (Hypotheses 1-2). Finally, I look at the mechanisms through which these changes in private and public crime take place – examining how prevention and law enforcement change in advance of elections (Hypothesis 3).

2.2.1 Impact of Upcoming Elections on Crime

Existing frameworks that study the role of the police in the crime process focus only on one aspect of their behaviour – their decision to respond once a crime has occurred. In this setting, the only decision that can be made by the police is whether to record and investigate an infraction or not, given that it has occurred. However, the change in criminal and political behaviour during elections may be anticipated by the police. Under certain conditions, they may even take proactive steps to control and prevent criminal activity during the election period.[11] In this sense, the police have two potential instruments they could use to control crime and violence – the decision to prevent crime and the decision to enforce the law. Enforcement, here, refers to the decision of the police to respond to a crime, given that it has occurred. The enforcement process begins with the police registering a victim's complaint, and is followed by the investigation of the crime, arrests, and prosecution.

To study the impact of upcoming elections on the crime process, I adapt an existing framework from Donohue & Levitt (2001), who present a stylized model of timing in the occurrence of a crime. For a crime to occur, three actions must take place. First, a criminal opportunity arises, and the criminal decides whether or not to commit

[11] Meloni (2018) notes that the decline in crime during elections might be due to the effect of more patrolling, etc., brought on by political incentives to show reduced crime levels, but he is unable to either measure this channel or provide evidence for its operation.

the crime. Second, if the crime is committed, the victim chooses whether or not to report this to the police. Finally, if the crime is reported to the police, the police investigates the crime, and takes one of the following actions: a true arrest is made, a false arrest is made, or no arrest is made. If the crime is not reported by the victim, then the crime is not investigated and the criminal is not punished.[12] In adapting this framework to the question of violence against women in India, Iyer et al. (2012) adapt the final step of this framework to focus on whether police choose to record a crime or not when a victim makes a complaint. The recording decision, in their setting, depends on various factors, including the gender of the local councillor – police are more likely to record crimes against women when the local councillor is a woman.

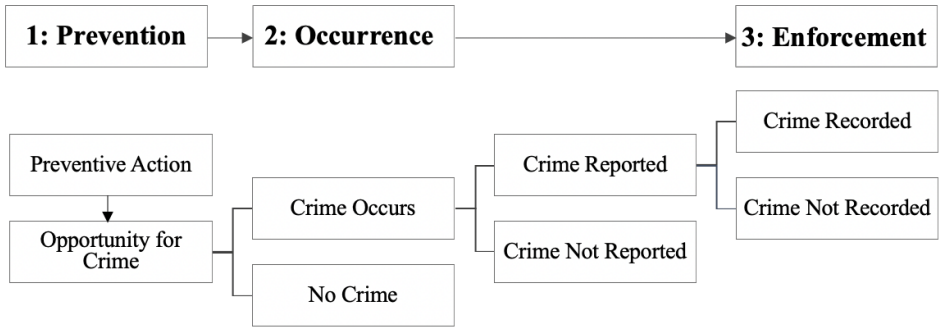
I adapt this framework by including an additional stage to the framework suggested by Donohue & Levitt (2001) and Iyer et al. (2012). This stage, called *Prevention* (or *Deterrence*), refers to police activity that is preventive in nature, i.e., it is aimed at reducing the opportunity for the occurrence of crime. This kind of preventive work then has an effect on the likelihood (conditional probability) of the criminal committing the crime.[13] Once a crime has been committed, and is reported by the victim, then in the following stage, called *Enforcement*, the police can choose whether and how they will respond to the occurrence of a crime. In this setting, an upcoming election can affect all stages of the framework presented in Figure 2.1.[14]

[12] In Donohue & Levitt (2001), the race of victim determines the likelihood that a true or false arrest is made, conditional on the crime being reported. The decision to report itself depends on the race of the victim as well as the race of the police officer.

[13] Crime may occur whether the preventive activities have taken place or not – it is just that the likelihood of crime might decrease after preventive work by the police. I also do not make any claims about how effective this preventive work is.

[14] In this empirical framework, I do not analyse the incentives of the victim to report or not report crime. It is possible that the election period might change the likelihood of crime reporting by victims, for example, victims might be less likely to report crimes committed by the incumbent. However, I assume that the election does not change the likelihood of victim reporting.

Figure 2.1: Stylized Model of Timing



Notes: In this framework, there is an additional stage for preventive work. This stage gives the police an additional tool for affecting crime, in addition to the enforcement decision, depicted here by the decision to record a crime or not.

2.2.2 Changes in Prevention and Enforcement during Elections

2.2.2.1 Crime Prevention by the Police

The police may change the nature of their preventive activity during elections for a few possible reasons. First, they may be able to anticipate an increase in violence during elections and may take action to prevent this. Second, the change in intensity of preventive activities by the police during elections may also be driven by institutional constraints that might not be present at other times and in other contexts. Bureaucrats cannot be certain of who will be in power once the election is complete, and display career concerns, wherein they are driven by the outcomes of tasks they are mandated to perform (Dewatripont et al., 1999; Alesina and Tabellini, 2008). Third, in this particular context, the election period entails a change in the structure of the government, as bureaucrats are no longer answerable to local politicians, but to an independent body, which is relatively more strict in terms of the performance review of bureaucrats. As is explained further in Section 2.3, the Election Commission of India is in control of the police during elections, with all officers reporting to the officials deputed by the EC to the district – the observers – rather than the elected government, which is put into abeyance. There may be career concerns amongst the top administrative and police officials whereby a negative comment made by the EC about an individual's (lack of) effort, measured by preventive ac-

tion, has important consequences for their future careers and postings (details can be found in Section 2.6.1). The measures of police performance at this time may be based on metrics laid down in terms of preventive activity, such as the number of preventive arrests, seizure of arms, etc., which might lead to the police focusing on meeting such targets. Finally, increases in preventive activity may be politically driven, either to reduce the incidence of certain kinds of non-political crimes and enhance the appearance of politicians' competence, or as a tool to target political opponents prior to elections.

2.2.2.2 Law Enforcement by the Police

There is widespread agreement that official crime statistics, across countries and across time, under-represent the actual levels of crime in society as the police does not fully enforce the law, in that it does not record all complaints of crime that it receives.[15]

The framework above shows that fewer (greater) crimes being recorded in official statistics could reflect both fewer (greater) occurrences of crime or fewer (greater) recording of crime occurrences. The changes in both the public and private offences are based on the interaction of actual changes in the occurrence of crime (stage 2 of the framework presented in Figure 2.1), as well as changes in the recording of crime (stage 3 of Figure 2.1). There may be cases where there is a change in recording levels for a given level of occurrence of the crimes. For example, for a given level of traffic violations, more cases may be registered, or, for a given level of domestic violence, fewer cases may be registered.

Disentangling the role of actual occurrence versus enforcement (recording) effects is

[15]This kind of under-enforcement is not driven by 'low state capacity' in the sense that the right incentives (such as the election) can lead to higher levels of enforcement. It is also not an 'intentional and revocable non-enforcement of the law', as analysed by Holland (2016), where a political choice to not enforce the law is made. As discussed in Wilson (1978), one of the most important reasons for the general under-enforcement of the law is that, as the police recognizes, public opinion would not tolerate a policy of full enforcement of all the laws all the time, which is what makes enforcement so discretionary.

difficult in any situation, but is particularly more difficult during the election period. Data that is used to triangulate administrative crime records, for example, survey data and crime victimization surveys, are collected over longer periods of time and may reflect individuals' general perceptions or experiences of crime as opposed to their experiences during the election period specifically.

The extent of under-enforcement of crime is not constant, and depends on various factors, such as the identity of the victim or the perpetrator (Tellez et al., 2020). It also depends on the nature of the offense itself – for example, the literature recognizes that under-enforcement is less likely for the most serious offences (Wilson, 1978; Iyer et al., 2012). This may be because of departmental and individual officer incentives, but also because under-enforcing serious crimes could lead to further incidents if not responded to appropriately. Finally, there may be political incentives for over- or under-enforcement of certain kinds of crime or crimes by or against certain individuals. Section 2.5 provides suggestive evidence from qualitative interviews to describe the nature of changes in enforcement activity during the election period, where the enforcement of crimes related to public order tends to increase and the enforcement of other crimes tends to decrease.

Finally, how does the change in prevention affect enforcement? Given the incentives for an increase in preventive activity, there are two possible impacts that this could have on enforcement. In a context where the same agency is responsible for both preventive policing and enforcement during elections, the increase in preventive work might be offset by a decrease in enforcement of crimes that are neither visible nor serious. Holmstrom and Milgrom (1991) highlight that incentivizing civil servants based on performance will lead to a shift in attention away from tasks that cannot be easily measured to others that can be. This may be particularly true and counterproductive in the case of policing (Prendergast 2001, Banerjee et al., 2021). For example, Prendergast (2001) shows that attempts to subject the Los Angeles Police Department to external oversight led to a sharp reduction in the effort exerted by

them on their crime-fighting activities, in an attempt to avoid investigation. Criminals, who have the most information on the effort exerted by the police, also have the least incentive to complain.[16]

Based on the framework outlined above, there is an ambiguous impact of elections on crimes against public order (riots, drunken fights, etc.). Intuitively, this is the case as the kinds of crimes that affect public order are the most common forms of political mobilization during electoral campaigns – large-scale rallies, marches, and other gatherings of individuals, so the police have a greater incentive to prevent and enforce violations of such crimes. While increased prevention might reduce the occurrence of such crimes, increased enforcement would increase the recording of such crimes, and the net impact is ambiguous.[17] On the other, crimes against individuals, including crimes against the human body (homicide, assault and battery), property crimes (robbery, theft, break-ins), crimes against women or children, would decrease, driven by an increase in police prevention, decrease in police enforcement and recording, and a shift in criminal activity towards more political activity. These crimes are not, by their very nature, political or electoral – for example, some murders occurring at this time might be political, others might not be. In terms of mechanisms, I predict that there is an increase in preventive work that may reduce the opportunity for crime in the first place.

Hypothesis 1: There is an ambiguous impact of elections on the incidence of crimes against public order.

Hypothesis 2: There is a decrease in the incidence of individual crimes related to offences against the body, offences against property, and crimes against women and

[16] On the other hand, preventive and enforcement activities can be complementary in the sense that higher effort exerted on prevention might reduce the occurrence of crimes, if preventive activity is effective.

[17] Electoral offences are not included in the category of crimes against order as they may or may not be related to public order (for example, disqualification from election). Electoral offences are expected to increase during the election period given an increase in political mobilization during this period compared to the non-election period.

children, at the time of elections.

Hypothesis 3: There is an increase in preventive work by the police at the time of elections.

I also suggest that there is a shift in enforcement activity by the police at the time of elections away from individual crimes towards crimes against public order and discuss this further using suggestive evidence from qualitative interviews.

Table 2.1: Hypotheses

H#	Outcome	Examples	Predicted Direction	Mechanism
1	Crimes against public order	Riots, drunken fights	?	$\uparrow$ in preventive work, $\uparrow$ in enforcement
2	Crimes against the body	Homicide, assault, battery	$\downarrow$	$\uparrow$ in preventive work, $\downarrow$ in enforcement
2	Crimes against property	Robbery, theft, break-ins	$\downarrow$	$\uparrow$ in preventive work, $\downarrow$ in enforcement
2	Crimes against women	Domestic violence	$\downarrow$	$\downarrow$ in enforcement
3	Preventive work	Patrolling	$\uparrow$	Incentives for preventive work

Notes: An increase in preventive activity works to reduce crime.

2.3 Institutional Context and Data: Managing and Policing Elections in India

Elections in India are mega-events. As democracy plays out at the grass-roots of a large country, a vast administrative machinery is mobilized to prepare for a large electorate (over 900 million electors in 2019) to cast their votes. The most recent 2019 national elections involved over 600 million voters across 1,035,918 polling stations, voting for 8,040 candidates in 7 election phases spread across 39 days (Chowdhury, 2019). More than 10 million election officials were involved, as well as 2 million state police officials and 300,000 paramilitary personnel (Suri and Gupta, 2019; Press Trust of India, 2019).

At the centre of all this activity is the Election Commission (EC) of India, "one of the most powerful electoral regulatory bodies in the world" (Ahuja and Ostermann, 2018). The EC, established as an independent body by Article 324 of the Indian Constitution, manages and oversees all elections at the national and the state levels. With a staff of just about 400 employees (Chowdhury, 2019), it is responsible for all aspects of the election – from transporting the Electronic Voting Machines (EVMs) securely across the country, to implementing the Model Code of Conduct which regulates the behaviour of candidates and parties during the campaign; from appointing election observers in districts across the country, to even adjudicating election-related disputes.

During an election in India, little government business takes place, and the EC has nearly full control of the state (Ahuja and Ostermann, 2018). Once the elections are announced, the police, paramilitary forces, and the entire administration come under the jurisdiction of the Election Commission (Quraishi, 2014). They report directly to the EC, which is also in-charge of personnel deployment and transfers at this time. The EC uses the existing government machinery to fulfil its numerous

responsibilities, including ensuring that elections are safe and secure, and that the role of 'muscle power' in political campaigns is minimized.

Elections in India have frequently been marred by violence (Verma, 2005). This ranges from soft forms of voter intimidation, to deadly riots and the deluge of booth-capturing, where armed intimidation and force are used to seize control of polling stations and control balloting (Gilmartin & Moog, 2012). There is general agreement that serious levels of violence, particularly deadly violence, have declined in recent elections compared to past decades (Daxecker, 2020). While instances of booth capturing still occur (Johari, 2014), they are perceived as being less frequent compared to before (Mendiratta, 2010; Quraishi, 2014). However, instances of crime and political violence continue to abound, and we know very little about the number of criminal and electoral violations that take place during election times in India, beyond instances of visible booth-capturing, political murders, or riots, as limited related information is published in a systematic manner by the government or the EC (Verma, 2005). Several of the areas that are vulnerable to electoral violence are those with ongoing armed conflict, such as Jammu and Kashmir, the North-east, areas affected by left-wing insurgency, and states with long histories of violent political rivalries such as Kerala and West Bengal. West Bengal, in particular, is known for electoral and political violence, including instances of both organized violence and spontaneous attacks. In the state elections of 2016, high levels of mob violence were recorded, dominated by clashes between party workers and among political rivals (Pollmann and Purohit, 2019; Nath, 2020). Violence also takes part along communal, caste-based, party-based lines, as well as through patronage-based networks. Berenschot (2020), for example, argues, using data from India, that politicians are able to successfully foment violence in areas where citizens depend on ethnicized patronage networks, which provide both the incentives and the infrastructure to organize violence.

To undertake preventive work and maintain law and order during election times, the

EC relies on the use of the local police, who are also in charge of crime administration. Public order and policing are state subjects in India's federal structure, which means that (in non-election periods) the elected state government, rather than the national government, is responsible for the prevention, detection, registration, and investigation of crime and prosecution of criminals. As per the framework for administration of crime in India, a First Information Report (FIR) is registered by the police when they receive information about a criminal offence. A single FIR can contain charges of multiple offences. Once a FIR has been filed, the police begin the process of investigation.

Criminal cases can be registered across a myriad range of codes and laws. The most important of these is the Indian Penal Code. Originally enacted in 1860, it is the official criminal code of India, covering all substantive aspects of criminal law. The IPC is divided into 23 chapters and over 500 sections covering a wide range of offences related to public order, bodily crime, property crime, and other kinds of crimes. 74% of all crime in the data is registered against the IPC. In addition, the Criminal Procedure Code (CrPC) provides the framework on criminal administration and procedure, including powers of the police and courts, and rules around arrests, warrants, summons, and investigations. Finally, governments at both the national and state levels have enacted laws which regulate various aspects of society, security, and the economy, and include criminal provisions. Examples of these laws include the Dowry Prohibition Act, 1961, the Prevention of Corruption Act, 1988, the Scheduled Caste and Tribe (Prevention of Atrocities) Act, 1989, and the Explosives Substances Act, 1908. There are over a 1,000 such laws in addition to the IPC and the CrPC. 26% of all crime is registered against these laws and the CrPC.

With the announcement of elections, the entire police machinery of the state comes under the purview of the EC. Under the direction of the EC, several preventive steps that the state administration can take under law are invoked to secure the election

process and ensure the maintenance of law and order (Mendiratta, 2010). The Criminal Procedure Code (CrPC) provides the legal basis for the use of preventive action and detention by the police. The police detain suspected criminals as well as those with existing criminal records for the duration of the elections under the preventive laws. Those who are suspected of causing disruptions are served notices under sections such as 107, 109, and 116 of the Code of Criminal Procedure, under which they are 'bound over' (Verma, 2005). As per these sections, the police obtain a legal undertaking ('bond') from these individuals to not indulge in criminal activity or violate the law, and these bonds are executed in court (Mendiratta, 2010). If the individual then commits a crime, he then has to pay a fine and legal action may be taken against him.[18] In more serious cases, if individuals continue to violate the law, preventive arrests can be made under sections 149 and 151 of the CrPC (Shukla, 2010).

In addition to preventive action under the CrPC, a number of special drives are launched by the police from the time that the elections are announced. First, arms licenses are temporarily suspended and firearms are deposited with the police. Illegal arms and ammunition is seized. Arms licenses of persons, particularly those released on bail, having a history of criminal offences, or previously involved in rioting at any time, but especially during elections, are reviewed (ECI, 2014; Quraishi, 2014). Similarly, illegal liquor and illicit cash is seized. The sale of liquor is regulated and banned close to the date of the poll and the date of counting (Quraishi, 2014). To check the movement of arms, liquor, cash, and criminals, and prevent smuggling, inter-state and intra-state movements of trucks and commercial vehicles are controlled (Quraishi, 2014). The police also proactively place check-points on roads and state borders (Verma, 2005). Finally, the investigation and prosecution of pending election-related cases is expedited. Pending non-bailable warrants for any

[18] Offences registered against these preventive sections are not technically crimes, and the Court has given orders to not include them in the crime data, but the level of compliance with this order has been low. However, these 'offences' are what helps to understand the change in preventive activity by the police during elections.

crimes, not just those related to elections, are executed and progress is monitored by the EC.[19] Overall, an elaborate process of planning and preparation to secure the election takes place under the supervision and monitoring of the EC.

2.3.1 Data

There are three main sources of data that I use in this paper – administrative crime data, information on election notifications, and third-party data on political violence from ACLED. Together, these three sources of data are able to provide a very detailed understanding at a fine-grained temporal level of the impact of upcoming elections on crime in India in the 2008-2019 period. In addition, I also use data from interviews conducted with elite policymakers and officials.

2.3.1.1 Administrative Crime Data

I obtain an administrative dataset of case-level crime data for over a decade from the National Crime Records Bureau (NCRB). This dataset contains information on every FIR recorded in 14,970 police stations across 33 states and Union Territories (UTs) in the January 2008-September 2019 period. This case-level data has been recorded in the electronic Crime and Criminal Tracking Network System (CCTNS) adopted by Police Departments across the country. This dataset contains information on the date of the crime, the acts and sections under which the complaint was registered, the police station where the crime was registered, and in some cases, the location and motive for the crime.

In this paper, I collapse the case data into a panel at the police station-day level. The availability of detailed information on the date, nature, and location of crime

[19] P36: "All the pending warrants, at the police station level, they start being reviewed, and these run into the thousands. In the police stations, in their normal working, it is the case that if there is no pressure on them, then they will not execute warrants, especially if it is of the local *gunda*. What they do is that on the basis of the warrant, they enter into an arrangement where the *gunda* gives them a cut and they never enforce the warrant."

within a district has several advantages. First, compared to event data on political violence, the administrative crime data covers a more broad range of crimes that may or may not be related to an election, but are of interest since the same state police is responsible for both election security and day-to-day crime administration. Second, administrative crime data is able to capture incidents that are unlikely to be captured in media-reported conflict data, either because of the nature of the crime (for example, petty theft or threat), or because of the location, as media sources might be less likely to cover issues from the hinterlands (Oberg & Sollenberg, 2011). Finally, the availability of information on a daily basis can help us understand trends in narrow sub-periods within an election period. These sub-periods are described in Section 2.3.1.2.

The main sample for my analysis uses the full sample of all police stations in the country. I also show the results using a partial sample of split police stations (those that can be uniquely assigned to an assembly constituency). Using the partial sample allows me to look at cases where the election schedule varies across constituencies within a given state, rather than being uniform across states, for example in the case of by-elections.[20]

2.3.1.2 Data on Election Notifications

In India, the EC publishes the election schedule, which includes information on the most important dates and deadlines within the election period, for example, the date on which the EC formally notifies the election ('issue of notification'), the date before which candidate nominations must be filed, the day of voting, the date on which votes are counted and results are declared, and so on. The election period as defined by the EC begins with the announcement of the election schedule and continues until the official date on which the election is completed. I obtain information on the election notifications from the official announcements of the EC

[20]For further information on matching of police stations to assembly constituencies, please refer to the data section of Chapter 3.

which I manually collect from their website, and where information is not available, I obtain it from the press releases published on the website of the national Press Information Bureau.[21]

Typically, the official election period lasts 66.75 days.[22] The official election period is distinct from the election period more generally understood, which can begin a few months in advance when informal campaign activities and electioneering begins.[23] Even within the official election period, there are different levels of political, criminal, and preventive activity, determined by the ongoing phase of campaigning and polling. The various official sub-periods and their average duration is shown in Table 2.2.

Table 2.2: Sub-Periods within the Election period and Duration

	Period From	**Period To**	**Duration**
1	Date of announcement	Issue of notification	22
2	Issue of notification	Last date for nominations	7
3	Last date for nominations	Scrutiny of nominations	1
4	Scrutiny of nominations	Last date for candidate withdrawal	2
5	Last date for candidate withdrawal	Date of poll	15
6	Date of poll	Counting of Votes	18
7	Counting of Votes	Date of completion of election	4

Notes: Duration represents the average length of the sub-period (number of days), where the average length has been rounded to the nearest whole number. Number of Observations: 139.

In addition to the sub-periods defined in the election schedule, a 'silence period' comes into effect 48 hours before the (end of the) poll – no campaigning is allowed to take place within this period as per the Model Code of Conduct, which regulates the campaign behaviour by political parties. I obtain notification information on all state, national, and by-elections in the 2008-2019 period. The sample for the main analysis in this paper consists of 77 state elections in the 2008-2019 period, with

[21] In a few cases dates initially announced in the schedule were subsequently changed in further announcements. I have incorporated these changes in my dataset.

[22] This is the average duration from the date of announcement of the election to the date of completion. In 3 out of 77 elections, the date of completion was missing, and was replaced by the date of counting. The average duration from the date of announcement to the date of counting is 62.66 days.

[23] I show that the results continue to hold even as the election window is expanded beyond the official period in robustness tests undertaken in Appendix 2.D.

an average of 7 state elections conducted each year. State elections conducted after May 2019 are not included in the sample.

Using the detailed election notifications data has the advantage that it allows me to study closely the changes in crime across various sub-periods within the election period. Labonne (2016) shows that the level of aggregation matters quite drastically for the ability to observe political business cycles – they are much more clearly visible in the case of quarterly data as compared to annual data. This is particularly important in the case of crime and violence, where outcomes can change very quickly. Using data from the notifications, I am able to identify electoral cycles in the run-up to the election much more closely as compared to looking at annual-level aggregates.

2.3.1.3 ACLED Data

The Armed Conflict Location and Events Data (ACLED) Project codes reported information from a wide range of local, regional and national sources on political violence, demonstrations (rioting and protesting) and select non-violent, politically important events (Raleigh et al., 2010). I use information on 59,745 events in India from the ACLED database over the duration 1 January 2016 - 31 December 2019. The project collects information on six types of events – battles, explosions/remote violence, violence against civilians, protests, riots and strategic developments.

As described above, there are concerns with reporting bias in media-based event databases. However, the data from ACLED is used for two specific purposes. First, it allows me to look at events that are not captured in police crime reports, such as battles or explosions, where paramilitary forces or insurgent actors may be involved. Second, the ACLED data helps me compare outcomes that are reported in both datasets, such as riots.

2.3.1.4 Qualitative Interview Data

In the absence of a crime victimization survey that can tell us about the true incidence of crime during elections, we do not have a good understanding of whether the changes in crime that are seen in the administrative and media-reported data reflect true changes in the occurrence of crimes committed and experienced. Similarly, there are no sources of data that can tell us about how the recording of complaints changes during elections. In order to understand the enforcement channel better, and to disentangle the role of prevention and enforcement, I use information from 15 qualitative interviews that I conducted with elite policy makers and frontline officials from India, including police officials of different ranks, politicians and political campaign managers, as well as EC officials. Further details about the interview methodology are given in Appendix 2.A.

Table 2.3 briefly summarizes the link between the theoretical hypotheses outlined above and the empirical analysis that I use to test the hypotheses. The relevant hypothesis and associated prediction is given in the first column. The column 'Category' presents the main categories of crime that I examine to test hypotheses H1, H2, and H3 - overall crime, electoral offences, offences related to public order, crimes against body, property, women, children, SC/STs, and preventive action. Details on which acts and laws are included in these categories is given in the 'Legal Instrument' column (and, where applicable, in column 'IPC Chapter'). The impact of election timing on the incidence of these laws is shown in the tables mentioned in column 'Table #', and the results derived from Tables 2.4 - 2.11 are summarized in column 'Results'.

Table 2.3: Summary of Hypotheses, Measurement, and Empirical Results

Hypothesis	Category	Table #	Legal Instrument	IPC Chapter	Results
General	Overall Crime	2.4	Case Count, Violation Count		↑
		2.8	Crime Count, Serious Crime Count		↓
		2.4	Non-Penal Code Crime Count		↑
	Electoral offences	2.4	Election Offences	IXA	↑
			Representation of the People Act		↑
H1 (?)	Public Order	2.5	Offences against Public Tranquillity	VIII	↑
			State Prevention of Defacement of Property Act		↑
			Motor Vehicles Act		↑
			State Noises Control Act		↑
		2.6	Battles, Explosions, Riots, Violence against Civilians		↑
		2.7	State Excise Act		↑
			Gambling		↑
			Prohibition		↑

Summary of Hypotheses, Measurement, and Empirical Results (continued)

Hypothesis	Category	Table #	Legal Instrument	IPC Chapter	Results
H2 (↓)	Crimes against Individuals	2.8, 2.9	Offences Affecting the Body	XVI	↓
		2.8	Offences Against Property	XVII	↓
			Offences relating to Document and Property Marks	XVIII	↓
		2.10	Offences Relating to Marriage	XX	↓
			Cruelty by Husband or Relatives of Husband	XXA	↓
			Dowry Prohibition		↓
			Domestic Violence [Non-IPC]		No change
			Immoral Trafficking		↓
			Indecent Representation of Women		No change
			Harassment		No change
		2.10	Child Marriage		↓
			Childrens Act		↓
			Juvenile Justice		No change
			Child Labour		No change
			Child Sexual Abuse		↓
		2.10	SC/ST Prevention of Atrocities		↓
H3 (↑)	Preventive Action	2.11	Criminal Procedure Code		↑
			State Gunda Acts		↑
			The Arms Act		↑
			Explosives Act		↑
			State Police Act		↑

Notes: '↑' and '↓' in the Results column indicate a significant increase and a significant decrease, respectively, as can be seen from the detailed results in Tables 2.4 - 2.11. 'No change' refers to a change that is not statistically different from 0.

2.4 Main Results

2.4.1 Empirical Specification

In this section, I provide evidence for electoral cycles in crime in India for the 2008-2019 period, looking at changes during the pre-election period. In addition to the variation in timing, I also look at variation in the types of crimes. I show results from fixed effects regressions looking at the impact of the election period on crime, including police station, week and year fixed effects. Following the literature on the estimation of political business cycles, I estimate regressions of the following form.

$$Crime_{it} = \beta_0 + \beta_1 Election_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{2.1}$$

The outcome variable, $Crime_{it}$, is the value of a particular kind of crime in police station i on day t. The variable $Election_{it}$ takes the value 1 if the date falls within the state election period for a police station i and 0 otherwise. All constituencies in a given state have an election at the same time. An election period is defined as the duration between the election schedule being announced ('date of announcement') and the date before which the election must be completed ('date of completion'). α_i and γ_t represent police station and week fixed effects, respectively.[24] Observations are at the day-police station level. Standard errors are clustered at the police station level to account for correlation of observations within a police station.[25] All regres-

[24]This data structure corresponds to the fuzzy design in the estimation of two-way fixed effects (de Chaisemartin and D'Haultfoeuille, 2020; Imai and Kim, 2021) as the treatment varies within group*period observations. Following de Chaisemartin and D'Haultfoeuille (2020), I replace the treatment effect with the average treatment effect within a group*period. Using the stata command 'twowaysfeweights', I find that the overall treatment effect estimates a weighted sum of 117,898 LATEs. 112,604 LATEs receive a positive weight, and 5,294 receive a negative weight. The sum of the positive weights is 1.0101954 and the sum of the negative weights is only -.01019541. Still, it is possible that the estimate of the coefficient of the treatment effect and the average treatment effect on the treated may be of opposite signs if the standard deviation of the treatment effect across the week*police station cells is equal to .02942423. However, in this case, treatment effect heterogeneity is not likely to affect the validity of the design since less than 5% of all the LATEs are negative.

[25]By clustering the standard errors at the police station level, I am able to account for any

sions use the inverse hyperbolic sine (IHS) transformation of the dependent variable. This transformation approximates the natural logarithm of the variable and allows me to retain all the observations that are zero-valued. The slope coefficient in this case can be interpreted as a percentage change (Burbidge et al., 1988).

I further aim to establish causal impact using a difference-in-differences (DiD) analysis for the states of Andhra Pradesh (AP) and Telangana (TS), presenting additional evidence that the results are not merely driven by time trends which may be correlated with state-wise election timing. Further details on the DiD design, including evidence in support of the identifying assumptions, as well as the DiD results, are presented in Appendix 2.C.

2.4.2 Main Results

This section presents the main results from the analysis. For clarity, I present only the estimates from the fixed effects regressions below. The results of the difference-in-differences analysis can be found in the Appendix.

2.4.2.1 Overall Crime and Electoral Crime

In Table 2.4, I present the overall impact of upcoming elections on the number of crime cases registered, including the number of FIRs filed, 'Case Count' (Column 1) as well as the number of violations, 'Violation Count' (Column 2). I also look at the change in other central, state, and local laws, including and excluding the Criminal Procedure Code - 'Non-Penal Code Crime Count' (Column 3), and 'Other Laws' (Column 4), respectively. The results show that there is a 5% increase in the number of cases registered per day (Column 1), and a 6% increase in the number of violations registered per day during the election period (Column 2), which correspond to effect sizes of 14.25% and 10.29%, respectively. The overall change is driven by an increase

temporal correlation in crime within the cluster.

in non-penal code crimes (effect size = 39.38%).

Electoral law in India is governed by the Representation of the People (RoP) Acts of 1950 & 1951, along with its subsequent amendments. This Act lays out the law relating to the conduct and administration of the election, from the qualifications of candidates and conduct of the poll, to the regulation of expenses and the definition of corrupt electoral practices (Gilmartin & Moog, 2012).[26] In addition, there are offences in the penal code relating to election offences, such as bribery and illegal payments in connection with an election.[27] Columns 5 and 6 of Table 2.4 show that there is a significant increase in election-related violations, which are more than 35 and 12 times the non-election period mean, respectively.

While the total number of non-penal code offences increase, there is huge variation among the 1000+ Acts that are included in this category. Acts that relate to organized crime, policing, weapons, prohibition, excise, gambling, even traffic accidents go up significantly, pointing towards greater proactive state action, regulation, and policing. On the other hand, offences relating to crimes against women, children, and SC/STs decline significantly.

[26]The relevant Acts include multiple amendments, including those of 1957, 1988, and 1989.

[27]However, these laws only look at violations of the electoral law related to the conduct of elections, and do not regulate all kinds of election-related crimes. For example, an election-related murder is not recorded against any of these sections. Instead, section 302 of the penal code, on homicides, is invoked.

Table 2.4: Impact of Election Periods on Main Outcome Variables in Full Dataset

	(1) Case	(2) Violation	(3) Non-Penal Code	(4) Other Laws	(5) Election	(6) RoP Act
Election Period	0.0587***	0.0610***	0.0863***	0.0264***	0.00700***	0.00875***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Constant	0.411***	0.593***	0.219***	0.182***	0.000201***	0.000729***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56302160	56302160	56302160	62232857	55278151	9777696
Mean	.412	.593	.219	.182	0	.001
Std. Dev.	.679	1.001	.573	.532	.016	.032
Effect Size (%)	14.25	10.29	39.38	14.45	3582.8	1215.96

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the full dataset of all police stations. The dependent variables in Columns 1-6 refer to the number of police complaints filed, the number of criminal violations, the number of non-IPC violations, the number of violations of state and local laws, the number of electoral violations under Chapter IXA of the IPC, and the number of cases registered under the Representation of People Act, respectively. The sample mean and standard deviation of the dependent variable in the non-election period are shown. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Column 5 does not include data from the erstwhile state of Jammu and Kashmir as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

2.4.2.2 Crimes Related to Public Order

Within the category of cases related to public order, some of the most important are offences are those 'against the public tranquillity', including unlawful assembly, affray, riots, and provocation on the grounds of religion, etc., with an intent to cause riots. There is a significant increase in these cases in the election period (Column 1 of Table 2.5). The associated effect size is 2.23%.

Another aspect of crimes related to public order is the effort of the administration to ensure that 'a general atmosphere of public order' is maintained. This is reflected in increases in the incidence of cases related to traffic violations, defacement of public property, and noise pollution, seen in Table 2.5.[28] For example, the incidence of cases of destruction of public property is 58.74% higher as compared to the non-election period mean.[29]

[28]Motor Vehicles includes The Motor Vehicle Act 1988 (Amendment 2015); The Motor Vehicles Act, 1988; Motor Vehicle Act, 1954; and Motor Vehicles (Maharashtra Amendment) Act, 1976.

[29]Section 2.5.3 explores the extent to which the increase is driven by actual versus recorded changes in these crimes. Results suggest that even though part of the increase in the incidence of such violations is driven by an increase in political and criminal activity, it is also partially driven by higher enforcement of cases related to noise pollution, traffic violations, and defacement of public property at this time.

Table 2.5: Impact of Election Periods on Daily Count of Order-related Violations

	(1) Public Tranquillity	(2) Defacement of Public Property	(3) Motor Vehicles	(4) Noise Control
Election Period	0.000556***	0.00146***	0.00144**	0.00100*
	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.0248***	0.00247***	0.0501***	0.0125***
	(0.000)	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Observations	55278151	42547009	43904888	2710179
Mean	.025	.002	.05	.013
Std. Dev.	.218	.056	.299	.143
Effect Size (%)	2.23	58.74	2.86	7.96

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the full dataset of all police stations. The dependent variable in Columns 1-4 refer to the violations related to Public Tranquillity (Chapter VIII of the IPC), state Defacement of Public Property Acts, the Motor Vehicles Act, and state Noise Control Acts, respectively. The sample mean and standard deviation of the dependent variable in the non-election period are shown. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Column 1 does not include data from the erstwhile state of Jammu and Kashmir as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

Table 2.6 shows the impact of the election period on outcomes of political violence, as measured by the ACLED data. The number of events associated with battles, explosions, riots, strategic developments, as well as violence against civilians increase during the election, and the number of protests decrease.[30] The effect sizes of changes in riots and violence against civilians are 63.53% and 57.74%, respectively. Given that the administrative crime and ACLED databases follow different inclusion criteria as discussed previously, I do not combine the two datasets in my analysis. However, as can be seen, the results from the ACLED data are consistent with the results from the administrative data, in particular, the 'Offences against Public Tranquillity' shown above (Column 1 of Table 2.5).[31]

Finally, Table 2.7 shows the increase in the incidence of cases related to state excise acts, which regulate the movement of goods, including liquor, acts related to the prohibition (consumption and regulation) of alcohol in the country, and acts that regulate gambling. The increase in cases (effect size) of excise, gambling, and prohibition-related acts is 68.93%, 9.11%, and 10.47%, respectively.[32]

[30]The decrease in the number of protests could be possibly explained by the increase in alternative forms of political mobilization as well as a decrease in the number of permissions given by the police for protests during the election period.

[31]The increase in riots is relatively larger in the ACLED data, which may point towards underrecording of riots in the administrative data.

[32]Certain states in the country have regulations prohibiting alcohol at all or certain times of the year.

Table 2.6: Impact of Election Periods on Daily ACLED Count and Fatalities

	Election Period	Constant	Observations
Battles	0.000300***	0.000699***	4088333
	(0.00007)	(0.00000)	
Explosions	0.000121***	0.000191***	4086164
	(0.00004)	(0.00000)	
Protests	-0.00201***	0.00938***	4124569
	(0.00030)	(0.00001)	
Riots	0.00135***	0.00211***	4094819
	(0.00016)	(0.00001)	
St. Dev.	0.0000901**	0.000143***	4085972
	(0.00004)	(0.00000)	
Viol. Civ.	0.000353***	0.000605***	4088117
	(0.00007)	(0.00000)	
Battles Fatalities	0.000198***	0.000474***	4088333
	(0.00008)	(0.00000)	
Explosions Fatalities	0.000100**	0.0000507***	4086164
	(0.00004)	(0.00000)	
Protests Fatalities	0.00000575	0.0000166***	4124569
	(0.00001)	(0.00000)	
Riots Fatalities	0.000107***	0.000143***	4094819
	(0.00003)	(0.00000)	
St. Dev. Fatalities	0.00000500	0.00000316***	4085972
	(0.00001)	(0.00000)	
Viol. Civ. Fatalities	0.0000860*	0.000293***	4088117
	(0.00005)	(0.00000)	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various outcomes of political violence as measured by the ACLED dataset at the daily-assembly constituency level using the full dataset. Rows 1-6 estimate the impact on the number of events. Rows 7-12 estimate the impact on the number of fatalities. St. Dev. = Strategic Developments. Viol. Civ. = Violence against Civilians. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. All regressions include constituency and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the assembly constituency level. No other covariates are included.

Table 2.7: Impact of Election Periods on Daily Count of Violations related to Alcohol and Gambling

	(1) Excise Act	(2) Gambling	(3) Prohibition
Election Period	0.0296***	0.0020***	0.0032***
	(0.00061)	(0.00029)	(0.00036)
Constant	0.0430***	0.0215***	0.0302***
	(0.00002)	(0.00001)	(0.00001)
Police Station FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Observations	38446583	41015071	48325461
Mean	.043	.021	.03
Std. Dev.	.246	.171	.21
Effect Size (%)	68.93	9.11	10.47

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the full dataset of all police stations. The dependent variable in Columns 1-3 refer to the violations of state Excise Acts, acts related to gambling, and acts related to the prohibition of alcohol and drugs, respectively. The sample mean and standard deviation of the dependent variable in the non-election period are shown. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

2.4.2.3 Crimes Against Individuals

Table 2.8 presents the changes in the IPC, 'Crime Count' (Column 1), and in the most serious sections of the penal code, 'Serious Crime Count' (Column 2), which decline during the election period. The definition of serious crimes follows that given by ADR (2014), and includes the most grave offences, such as homicide. Crimes targeting individual victims, such as crimes against body and property are the most common violations in the penal code, and constitute 56% of penal code violations. Offences affecting the human body include murder, culpable homicide, suicide, foeticide, hurt, restraint, assault, sexual harassment, rape, and kidnapping. Similarly, crimes against property include theft, extortion, robbery, dacoity, cheating, breach of trust, and trespass. Crimes against documentation and property marks include offences related to forgery, fraud, and counterfeiting.

The change in the incidence of these crimes during the election period can be seen in columns 3, 4, and 5 respectively, of Table 2.8. The decrease in body, property, and property marks-related crimes is 3.3%, 7.89%, and 9.98%, respectively, as compared to the non-election period average. The incidence of murders decreases by 4.88% compared to the daily non-election period average (Table 2.9). Murders are the most serious crimes against individuals, and are the least likely to be under-reported or under-recorded at any time. A decline in murders could point towards several different mechanisms – effectiveness of police preventive action during this period or a shift in criminal activity away from murders to other activity. In this sense, murders are a benchmark for the enforcement problem as there is likely to be no change in the enforcement of murder-related crimes.

Table 2.8: Impact of Election Periods on Daily Counts of Body and Property Crime

	(1) Crime	(2) Serious	(3) Human Body	(4) Property	(5) Property Marks
Election Period	-0.00966***	-0.0117***	-0.00731***	-0.0120***	-0.000911***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	0.458***	0.271***	0.221***	0.152***	0.00909***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Observations	56302160	55278151	55278151	55278151	55278151
Mean	.459	.271	.221	.152	.009
Std. Dev.	.9	.621	.561	.461	.131
Effect Size (%)	-2.11	-4.3	-3.3	-7.89	-9.98

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the full dataset of all police stations. The dependent variable in Columns 1 and 2 refers to the number of violations of the penal code and serious offences of the penal code (as defined by ADR (2014)). Columns 3-5 refer to the violations of the IPC Chapters on Offences against the Human Body (Chapter XVI), Offences against Property (Chapter XVII), and Offences relating to Documents and Property Marks (Chapter XVIII), respectively. The sample mean and standard deviation of the dependent variable in the non-election period are shown. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Data from the erstwhile state of Jammu and Kashmir is not included as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

Table 2.9: Impact of Election Periods on Daily Murders

	(1) Murder Count
Election Period	-0.000194***
	(0.000)
Constant	0.00397***
	(0.000)
Police Station FE	Yes
Year FE	Yes
Week FE	Yes
Observations	55098174
Mean	.004
Std. Dev.	.066
Effect Size (%)	-4.88

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on murders at the daily-police station level using the full dataset of all police stations. The sample mean and standard deviation of the dependent variable in the non-election period are shown. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Data from the erstwhile state of Jammu and Kashmir is not included as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

Further, we are interested in looking at the incidence of individual crimes against members of specific groups as this can tell us more about the vulnerability and access to justice for different groups. For example, we might not expect an increase in crimes against women and children due to the election. If anything, we might expect to see an increase in crimes against women due to political mobilization or an increased availability of alcohol. We should expect to see no changes in crimes against children due to political or criminal activity.

However, from the results in Table 2.10, we can see that there is a general decline in crimes against women and children during the election period. In the case of crimes against women, certain offences such as rape and foeticide are part of crimes against the human body, which decreases overall, as seen above. Specific chapters in the penal code specifically pertain to marriage-related offences and cruelty by husband or relatives, or domestic violence (rows 1 and 2, respectively, of Table 2.10). In addition to these offences in the penal code, governments over the years have passed other laws relating to the prohibition of dowry, domestic violence, trafficking, and harassment at the workplace. Most of the cases for domestic violence are filed under the penal code (row 2 of Table 2.10). Some of the cases can also be filed under The Protection of Women from Domestic Violence Act, 2005 (row 4).[33] As can be seen from Table 2.10 (rows 1-7), there is a decline in the incidence of crimes against women.

Similarly, there is a decline in the incidence of violations of laws that pertain to child marriage, child labour, child sexual abuse, child safety and juvenile offenders (rows 8-12 of Table 2.10).[34]

[33]Dowry acts include The Dowry Prohibition Act, 1961; Dowry Prohibition (H.P Amendment) Act, 1976; Dowry Prohibition (Orissa Amendment) Act 1975; and Dowry Prohibition (Maintenance Of Gifts Presents Bride And Bridegroom) Rules-1985. Immoral trafficking includes cases under the Immoral Traffic (Prevention) Act, 1956; Suppression Of Immoral Traffic In Women And Girls Act, 1956; and Suppression Of Immoral Traffic In Women And Girls (A And N Islands) Rules, 1958. Harassment includes cases filed under the Tamil Nadu Prohibition Of Harassment Of Woman Act, 2002 and The Sexual Harassment Of Women At Workplace (Prevention, Prohibition And Redressal) Act, 2013.

[34]Child Labour is regulated under The Children (Pledging Of Labour) Act, 1933; The Child Labour (Prohibition And Regulation) Act, 1986; and Child Labour (Prohibition And Regulation)

Finally, when it comes to groups such as caste and religious minorities, we might expect a change in the nature and magnitude of crime against them, particularly in the Indian context as a lot of political activity is based on caste and communal mobilization (Chandra, 2004). But in the absence of further information, we cannot further test these patterns of mobilization and how they relate to political and policing behaviour in the context of elections.[35] Row 13 of Table 2.10 shows that there is a decline in the incidence of crimes against individuals from SC/ST groups (effect size = 4.18%).[36] Appendix 2.H shows that there is no increase in crimes against women in the 6-month period prior to the announcement of the election, whereas there is an increase in crimes against SC/STs over a similar period.

2.4.2.4 Preventive Activity

The previous results show that there is an increase in crimes against public order and a decrease in other crimes against individuals during elections. The following section focuses on the changes in preventive activity by the police. As mentioned above, the Criminal Procedure Code provides the legal basis for the use of preventive action and detention by the police. It allows the police to obtain a legal undertaking from suspected criminals that they will not violate the law. In more serious cases, the police can detain suspected criminals and make preventive arrests (Verma, 2005; Shukla, 2010).

Table 2.11 shows that there is an increase of 9% in the execution of bonds and

Amendment Act, 2016. Cases of child marriage are filed against The Child Marriage Restraint Act 1929; Infant Marriages Prevention Act 1985 (1928 Amendment); Prohibition Of Child Marriage Act, 2006; and Chhattisgarh Children Marriage Prohibition Act 2007. Juvenile Justice Acts include The Juvenile Justice Act of 1986, 1997; Juvenile Justice (Care And Protection Of Children) Act, 2000; Chhattisgarh Juvenile Justice (Care Protection Of Children) Rules, 2003; Chhattisgarh Juvenile Justice Rules, 1988; and Juvenile Justice (Care And Protection Of Children) Act, 2015. Childrens Act includes The Children Acts of 1948, 1949, 1960; M.P. Childrens Act, 1970; U.P. Children Act, 1952; and The Goa Childrens Act, 2003. Cases of child sexual abuse are filed against The Protection Of Children From Sexual Offence Act, 2012.

[35]Data on hate crimes is not distinctly included in the data, and we do not have information on the identity of the victim.

[36]This includes cases filed under The Scheduled Castes And Scheduled Tribes (Prevention Of Atrocities) Act, 1989 and The Scheduled Castes And Scheduled Tribes (Prevention Of Atrocities) Amendment Ordinance, 2014.

Table 2.10: Impact of Election Periods on Daily Count of Crimes against Women, Children, SC/STs

	Election Period	Constant	Observations	Effect Size (%)
Marriage	-0.000265***	0.00167***	55278151	-15.87
	(0.0000)	(0.0000)		
Cruelty	-0.00152***	0.0143***	55278151	-10.61
	(0.0001)	(0.0000)		
Dowry	-0.00137***	0.00911***	36614174	-15.04
	(0.0001)	(0.0000)		
Domestic Violence	-0.000256	0.00164***	1496208	-15.7
	(0.0002)	(0.0000)		
Immoral Traffic	-0.000625***	0.00209***	13258367	-30.01
	(0.0001)	(0.0000)		
Indecent Representation	-0.00000350	0.00144***	1926332	-.24
	(0.0002)	(0.0000)		
Harassment	-0.00120	0.00898***	6218719	-13.46
	(0.0014)	(0.0000)		
Child Marriage	-0.000460***	0.00106***	6112388	-43.57
	(0.0001)	(0.0000)		
Children Acts	-0.000923**	0.00369***	878592	-24.77
	(0.0004)	(0.0000)		
Juvenile Justice	-0.000106	0.00143***	14070016	-7.4
	(0.0001)	(0.0000)		
Child Labour	0.000128	0.00156***	4702060	8.2
	(0.0001)	(0.0000)		
Sexual Abuse	-0.000807***	0.0104***	26064555	-7.73
	(0.0002)	(0.0000)		
SC/ST	-0.000241***	0.00579***	48539680	-4.18
	(0.0001)	(0.0000)		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various outcomes of crimes against women, children, and against SC/STs under the SC/ST (Prohibition of Atrocities) Act at the daily-police station level using the full dataset of all police stations. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Data from the erstwhile state of Jammu and Kashmir is not included in rows 1 and 2 as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

other preventive activity undertaken by the police under this code (effect size = 107.62%).[37] This is similarly the case with the Gunda Acts (Column 4 of Table 2.11), which were enacted by certain states to 'make special provisions for the control and suppression of Gundas with a view to the maintenance of public order' (U.P. Control of Gundas Act, 1970).[38]

Table 2.11: Impact of Election Periods on Daily Count of Preventive Activity

	(1) CrPC	(2) Arms Act	(3) Explosives Act	(4) Gunda Act	(5) Police Act
Election Period	0.0905***	0.0041***	0.0012***	0.0055***	0.0168***
	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.0841***	0.0111***	0.0015***	0.0031***	0.0596***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Observations	30329489	48023217	31216877	2340920	20305376
Mean	.084	.011	.001	.003	.06
Std. Dev.	.331	.13	.046	.069	.296
Effect Size (%)	107.62	37.07	86.58	175.71	28.1

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the full dataset of all police stations. The dependent variable in Columns 1-5 refer to the number of violations of the CrPC, the Arms Act, the Explosives Act, state Gunda Acts, and state Police Acts, respectively. The sample mean and standard deviation of the dependent variable in the non-election period are shown. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

In addition to preventive action that directly targets individuals who might be likely to incite violence or commit crimes, the police also undertakes special drives targeting illicit arms and ammunition, liquor, and cash, as described in Section 2.3. The

[37] I use all sections of the CrPC to examine the change in preventive activity since the code provides guidance to the police and courts on how to make summons, present warrants, undertake arrests, etc., and while this might not always be preventive, it relates to the administration of crimes, rather than being a crime in itself.

[38] *Gundas* roughly translates to 'anti-social elements' and are a distinct category of goons with connections to politicians or organized crime, as described by Ward (2011). State Gunda Acts include Rajasthan Control Of Gundas Act 1975; U.P. Control Of Gundas Act 1970; The Maharashtra Control Of Organised Crime Act, 1999.

efforts to control the availability and movement of arms and ammunition is reflected in an increase in cases registered against the Arms Act and the Explosives Acts (Columns 2 & 3 of Table 2.11).[39] The impact on the number of cases (effect size) of the Arms Act is 37.07%, the Explosives Act 86.58%, the Gunda Act 175.71%, and the Police Act 28.1% of the non-election period mean.

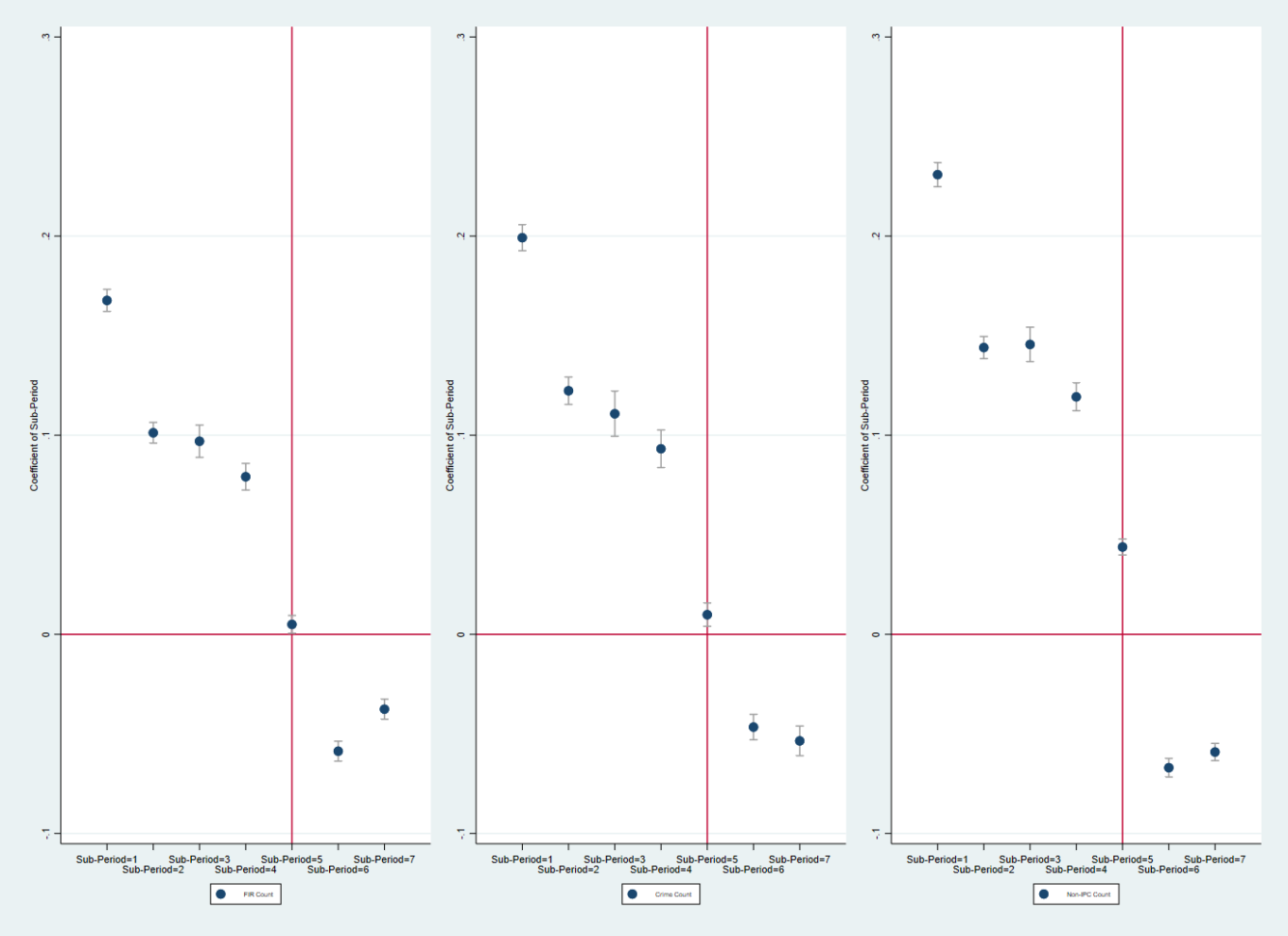
2.4.3 Heterogeneity in Timing: Sub-Periods Analysis

As discussed in Section 2.3.1.2, there are multiple sub-periods within the official election period. Sub-trends within the election period show that the changes during this period are themselves non-linear, even though they reflect the overall trends during the election period. In particular, the pre-poll and post-poll estimates move in opposite directions, as one would expect. These results provide additional evidence that the results are not simply capturing timing effects - in that election periods happen to coincide with periods of high preventive and non-penal code crime, and low crime and serious crime.

Figure 2.2 presents the changes in the case, violation, and non-penal code count within the election period. As can be seen, the incidence of cases and preventive sections increases until the date of the poll and decreases after that, compared to non-election periods, even though the official election continues. On the other hand, Figure 2.3 show that crime and serious crime (from the penal code) continue as in the baseline period until the date of the poll, when they dip sharply. After the poll, serious crimes are *higher* than baseline levels, whereas overall crimes continue to remain low.

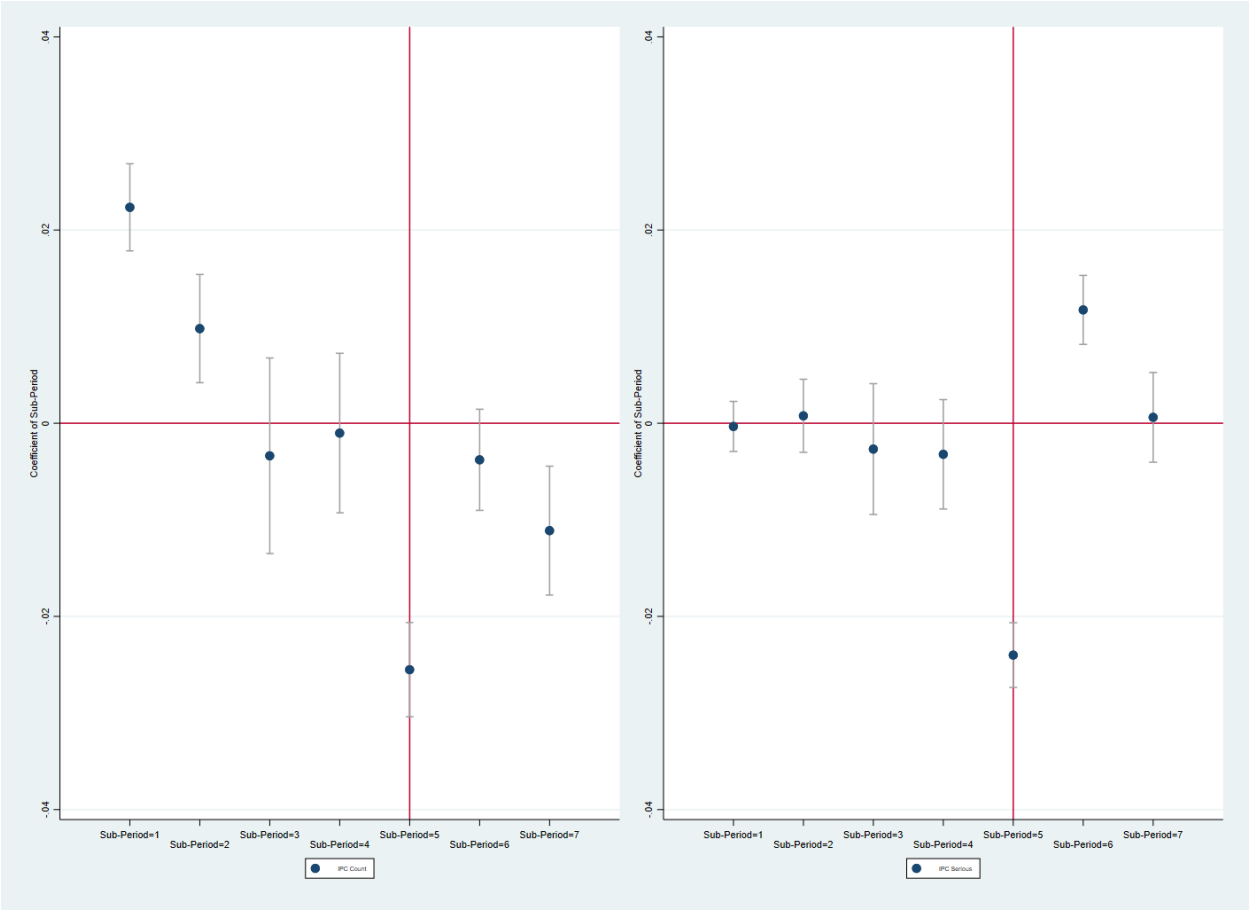
[39] Arms Act includes Arms Act 1959 & Indian Arms Act 1969. Explosives Act includes Explosive Substances Act 1908, Indian Explosives Act 1884 (2013, 2014 Amendments), Explosives Rules 2008.

Figure 2.2: Sub-Period Trends in Case, Violation, and Non-Penal Counts are Consistent with Overall Trends, even though Pre- and Post-Poll Trends Differ



Notes: The graph presents the coefficients of the sub-periods within an election period for the number of cases, violations, and non-penal code counts. The vertical line represents the polling period. The base period for comparison is the non-election period. Sub-period 1: Date of announcement - Issue of notification. Sub-period 2: Issue of notification - Last date for nominations. Sub-period 3: Last date for nominations - Scrutiny of nominations. Sub-period 4: Scrutiny of nominations - Last date for candidate withdrawal. Sub-period 5: Last date for candidate withdrawal - Date of poll. Sub-period 6: Date of poll - Counting of Votes. Sub-period 7: Counting of Votes - Date of completion of election. Crime count in the graph refers to the number of violations.

Figure 2.3: Most Changes in Crime and Serious Crime come during and after Polling



Notes: The graph presents the coefficients of the sub-periods within an election period for the count of the penal code and the serious penal code crimes. The vertical line represents the polling period. The base period for comparison is the non-election period. Sub-period 1: Date of announcement - Issue of notification. Sub-period 2: Issue of notification - Last date for nominations. Sub-period 3: Last date for nominations - Scrutiny of nominations. Sub-period 4: Scrutiny of nominations - Last date for candidate withdrawal. Sub-period 5: Last date for candidate withdrawal - Date of poll. Sub-period 6: Date of poll - Counting of Votes. Sub-period 7: Counting of Votes - Date of completion of election.

These changes are in line with what we might expect from the behaviour of the police in terms of an increase in preventive activity before the election, with a sharp drop-off immediately afterwards. Similarly, while there is no change in serious crimes for the most part, they dip sharply right before the poll, and increase afterwards, reflecting an increase in incidence or in enforcement, as the registration of cases previously pushed back may take place. However, there is no such sharp increase in the case of general crimes, which simply revert to non-election period levels as cases may remain un-enforced. Similar patterns hold in the partial dataset. The regressions results for both the full and partial dataset are shown in Tables 2.F.12 and 2.F.13 in the Appendix.

2.4.4 Robustness Checks

Finally, I undertake several robustness checks to establish the validity of the main results. I show robustness to the use of the partial dataset, which includes constituency-level matches for police stations. Using by-elections, I test that results are not driven by time trends. I test that the results are not being driven by particular states, or by periodicity (using weekly rather than daily data). I expand the election period beyond the official period, and show that the effects remain consistent over a longer period of time in the run-up to the election. I show that results are consistent to using national-level elections instead of state-level elections, and that they are robust to alternative levels of clustering of standard errors. These results are presented in Appendix 2.D.

2.5 Mechanisms: Occurrence vs Enforcement

What drives the changes in incidence of crimes that can be seen in the data? As per the framework described in Section 2.2.1, a change in the incidence of crimes could be due to either a change in the occurrence of the crime or a change in

its enforcement (recording, for example) by the police. To explore this further, I undertake qualitative interviews with police officials, politicians, political campaign managers, as well as Election Commission officials, as described in Section 2.3.1.4.

These interviews suggest three things. First, levels of enforcement seem to matter – some increases in the incidence of crime are driven by higher-than-usual levels of enforcement, and some decreases in the incidence of crime are driven by lower-than-usual levels of enforcement. Second, the change in enforcement levels is not constant for all crimes, but depends on the nature of the crime itself, for example, how serious and visible the crime is. Finally, the incentives of the police during this time seem to drive the changes in their enforcement, and this could be in line with the behaviour we would expect from multitasking bureaucratic agents as well as bureaucratic agents who collaborate with politicians in line with politicians' re-election incentives.

2.5.1 Changes in the Occurrence of Crime

Changes in the occurrence of crime are driven, as per the framework in Figure 2.1, by the opportunity for crime (preventive action) and criminal activity. For example, as one officer said, "Once we start checking for cash at check-points, and stopping people with a lot of cash, pick-pocketing will also go down as people carry fewer cash on them."[40] (P35) Officers from the police agreed that the police was much more active during the election period, but differed in their assessment of how their preventive activity affected the incidence of crime.[41]

[40]There are may be substitution by criminals in the kind of activity they engage in during elections. For example, they may move away from petty crime towards more politically-related crimes. Several interviewees from police and political backgrounds mentioned this. However, I did not interview any criminals.

[41]There is a limited understanding of the impact of preventive work on crime in the literature, especially when it comes to securing elections. Some exceptions are the work by Birch and Muchlinski (2018), and Smidt (2020). While there is a mixed set of opinions within the government about how effective the preventive action was in reducing crime during elections, this question is beyond the scope of this paper.

2.5.2 Decrease in Enforcement of Crimes against Individuals

Interviews suggested that there is a decrease in the enforcement of certain kinds of crimes, especially those that are not directly related to elections, are less visible, or of a less serious nature. Several interviewees believed that there is no real change in non-election related crimes at the time of elections.[42] To the extent that there is a difference when there is no change in occurrence, it can be accounted for by a decline in enforcement (here, the recording of crimes). Most interviewees agreed that recording of certain kinds of crime was likely to go down at the time of elections, and also elaborated on examples of crimes for which this might be true.

Qualitative evidence suggests that crimes against groups such as women tend to be under-recorded at this time. One police officer said, "Cases that may be related to senior citizens, domestic violence, etc. may be postponed for later." (P35) Several agreed that crimes against women, "cases like domestic violence, crimes against women are all likely to be under-reported." (P51) "Crimes against women also do not change, there are no differences in that. Neither do they increase, nor do they decrease, that has been my personal observation." (P91) said another. "Especially crimes against women – women are most likely to be among the sufferers during this time." (P32) Several agreed that sections related to domestic violence are some of the easiest to under-report, and mentioned that the scope of reconciliation is used as a way to discourage recording of crime. "In the case of Section 498A, domestic violence, there is always scope to do reconciliation, through counselling, etc., so in many cases, we wait to register the case. And this is sometimes used by our people

[42]No Change in Non-Election Crime: "Non-election related crime does not generally come down. There may be some minor variations. But many other issues, such as property issues, issues related to women, issues related to land, petty quarrels, husband beating wife, wife beating husband, all of these go on. It is only that crime related to political activity also increases." (P99) Another officer said, "The truthful answer is that not much changes on the ground. First, there are a few additional murders, etc., but most of the other crimes that are indirect, they are not reported. So reporting generally goes down." (P60) This was also thought to be the case for non-election-related murders. "There is no decrease in murders. Murders can happen for a 2-3 reasons – the first is loot-related. The second is related to existing enmities, and they continue as usual. The third is related to family issues, for example, illegitimate relationships. None of that changes, it keeps going on. There is no difference in that." (P91)

to not register the case or wait." (P51) "In cases like 498A, we try to mediate, try counselling, etc. These are delaying tactics, we tell them to come back in 3 months after counselling." (P32) "This is also the case with domestic violence, this is seen as within the context of the house." (P75), and so, victims might be asked to come back later.

More generally, the decrease in recording "is a staunch fact. It might be denied by a lot of people, but it is absolutely true. At the time of elections, the entire focus is on elections, so we will tend to overlook certain things," said a police officer. (P32) "It is possible that because there is so much crime already due to elections, some of the more routine or regular cases are not registered or given so much importance," said another. (P51) Others said that it was not just that there was a decrease in recording, the entire process of enforcement – investigation, arrests – becomes weaker for some crimes. When victims complain, an officer explained, "a few things could happen. They [the police] could register the complaint, but then say that don't expect any investigation, because there are no investigative officers present there anymore, so we will investigate later. Or they could say you give us an application, we will do an inquiry rather than register the FIR. Or if it is a really heinous crime, then the FIR will be registered, the investigation will be started, but arrests, etc. will be made later." (P75) Others emphasized the importance of the kind of crime. "At this time, a lot of times the cases cannot be finalized immediately. Because of the headache of elections, there is other activity going on. So depending on the gravity of the case, we decide whether to accept the case and act on it immediately or not. For example, if there is a case of gravity, we will do it. But if not, we will look at it after the election is done." (P20)

2.5.3 Increase in Enforcement of Crimes Related to Public Order

Qualitative evidence suggests that in addition to reducing the enforcement of certain crimes, the police also increase the enforcement of crimes related to public order. This means for a given level of occurrence of the crime, the police is enforcing the law more – registering more cases, making more arrests. For example, while the incidence of traffic violations might remain the same as before, police might be more likely to enforce existing laws and record violations that may not have been recorded during other periods. This might lead to higher levels of certain kinds of crimes.[43]

Interviews suggested that as the police becomes more active, and the election becomes the priority, enforcement of crimes related to public order goes up. Most interviewees agreed that there was an increase in the level of activity of the police, but disagreed about the extent to which it would reduce crime. "There is more enforcement as the police is hyperactive." (P51) "Police activity has increased." (P60) "The intensity of the action of police goes up. The visibility increases. So petty crimes are bound to go down, as this activity will act as a deterrent." (P32) "The enforcement of the [Model] code of conduct, which we do, is similar as well. Whatever violations of the code of conduct are there, they are recorded as increases in crime. However, I would not necessarily call them crime, it is more of a reflection of the situation at the time, the elections." (P51)

The police also seem to be more focused on the elections as that is the main priority for them. "The fact is that administration is more tight-gripped during election times, because at that time they are doing only election work. Everything else is put into abeyance, so the administration is more focused that there should be no trouble during the election." (P71) "The nature of policing changes completely right after elections are announced, maybe even 15-20 days before that. Everything

[43]This is what one of the interviewees referred to as "over-enforcement." (P48)

shuts down, the police have just one priority, which is to get elections done fairly and safely. I would actually expect that other kinds of crime also go down during this period." (P35) "I think the primary reason here is that the election is a very involving concept and everyone is deeply involved in the process. So other issues reduce a lot both in imagination and in priority." (P66) "And then enforcement also increases quite a bit. At other times, there are always so many other things going on, including VIP movement, routine work, sometimes COVID, sometimes the Kumbh [a large-scale religious event]. But at election time, the entire focus is on conducting a free, fair and peaceful election." (P66) All these point towards an environment where the police are more active than usual, and take additional steps not just to prevent crime, as could be seen in the previous section, but also to enforce the law more strictly, in the form of filing additional cases that they may not bother with in other times.

An erstwhile head of the EC writes in his book, "What the ECI did not allow was long motorcades, defacement of public property or blaring loudspeakers inconveniencing ordinary citizens. It is not the ECI that came up with these rules as they were already part of the local municipal and state laws. The ECI only enforced them. It is noteworthy that the same laws that are routinely flouted acquire sudden respect and compliance during the EC's 'rule'!" (Quraishi, 2014, p. 402) Another official from the EC agrees: "There are 2-3 things that the EC does in a very demonstrative way. This is just to provide a signal that now the election has been announced and *ab nizam badal gaya hai*," the old order has changed. "So one of the things they do, and in my experience, it has been very effective, is that there is a Prohibition of Public Place Defacement Act. As a part of this, all government offices, all hoardings, walls, are cleaned up. Many of them have huge posters of the Chief Ministers and the other ministers. The instruction is that within 24 hours of the announcement of the election, all of these should be removed. People see that hoardings with ministers' faces on them are being taken down, posters are being removed. A newspaper may print a photograph of a hoarding with the CM's face on

it being swept away, so that changes the entire perception of order." (P36) Similarly, on the increase in the number of cases registered under the Arms Act, the Motor Vehicles Act, and so on, he said: "Yes, there are acts for which it feels like their enforcement is done only at the time of elections, not at all at other times. The whole idea is that there is this belief that if you stop the small crimes, adopt a zero tolerance system, then the larger crimes will stop themselves." (P36) In the view of the EC, the reason that enforcing seemingly innocuous, non-violent laws, such as those related to defacement of walls and noise pollution, is important is because they help establish an orderly environment, in which people feel safe and secure in participating the electoral process.

2.5.4 Changes in Occurrence vis-à-vis Enforcement

When asked about which crimes are relatively easier or more difficult to under-record, interviewees, particularly those who were from the police, provided me with examples of acts and IPC sections for which under-recording is more or less likely.

"So mentally, whatever will not be asked about by the EC, and is not of a political nature, those kinds of cases will be relegated. Other things that are related to elections, such as Prevention of Corruption Act cases, etc. will not. Cases like fraud, for example, at an ATM, will be pushed back. Essentially, cases that will not be sensationalized, cannot be brought up in a campaign – such basic heuristics are used to prioritize." (P75) Another officer mentioned that "all of the actions that are overt actions are difficult to hide." (P51)

In providing examples of cases that would most likely always be registered, officials agreed that no under-recording was likely to take place in sections pertaining to murder, which are "impossible to hide" (P60). "If there is a murder, then this has a lot of gravity. ... Other grave crimes are like rape, POCSO [child abuse], or cases where the contestant from one party is kidnapped by the other party." (P20)

Other crimes that are considered difficult to hide include "grievous hurt, kidnapping, attempt to murder."[44] (P51)

Together, these interviews suggest that not all decreases in crime during elections are driven by the same factors. The extent to which changes in crime are driven by changes in actual occurrence versus changes in recording depends on the nature of the crime itself. The precise nature of this relationship remains a question for further research.[45]

2.6 Role of Bureaucrats' and Politicians' Motivations for Prevention and Enforcement

As mentioned before, the changes in prevention and enforcement by the police are consistent with two alternative explanations. The first is the role of multitasking bureaucrats who are motivated by career concerns that become salient under the Election Commission. The second is the role of collaboration between bureaucrats and politicians who could work together to increase prevention of certain kinds of crimes, such as individual crimes, while also targeting political opponents with preventive action. This reduces individual crimes even as incumbents are able to increase political violence in the form of riots with the cooperation of the police. For example, as Wilkinson (2004) shows, politicians in India both cause communal

[44]Since the the snowballing sampling method for the interviews was non-random, the responses suggest that social desirability bias is not a serious concern and, if anything, there is a greater role for changes in police enforcement in driving these results.

[45]We know from the literature that how serious a crime is matters for enforcement. In addition, I propose that under-enforcement is less likely for the more "visible" forms of crimes. This may be because of the role of the media (Besley & Burgess, 2002); it could follow from a "broken windows" theory of crime where visible defacement could be seen to lead to other kinds of crimes taking place (Wilson & Kelling, 1982); or from the importance of more "visible" public goods being provided (Mani & Mukand, 2007). Hence, the decline in non-visible, non-serious crimes is more likely to be driven by a reduction in enforcement rather than a genuine decline in the occurrence of such cases. This is especially the case if these crimes are not committed by 'criminals' per se and we don't expect a substitution of criminal activity to be driving them, for example, domestic violence or child abuse. It is similarly the case for an increase in the enforcement of non-visible and 'non-serious' crimes against public order, such as an increase in the number of traffic violations. However, I do not focus on this hypothesis in this paper and plan to study it in future research.

Hindu-Muslim riots, and have the power to prevent them through their control of the police. Whether they do so depends squarely on the intensity of local political competition and the electoral support of minorities.

Most of the literature on electoral cycles is concerned with the incentives and behaviours of politicians, notably, their desire to show improved performance in advance of elections on economic policy outcomes, including growth and spending.[46] However, crime is likely to be different from other economic variables in two ways – the direction of the incentive, and the attribution of performance by voters.

In the case of crime, both Ghosh (2006) and Meloni (2018) hypothesize that the declines in crime are driven by political incentives to show improved performance, by increasing public safety at the time of elections. However, this incentive is likely to run up against the political incentives for violence, discussed in the literature on electoral violence. This literature widely understands electoral violence as strategic, generated by the electoral incentives of political elites (Harish & Little, 2017; Höglund, 2009; Wilkinson, 2004; Daxecker, 2020). As per this literature, the strategic deployment of violence is an electoral tool used during political campaigns to influence the electoral process, including candidates and voters, with coercion, intimidation, or threats of violence, or through creating fear and disorder based on existing social cleavages. So, unlike in the case of spending and other economic policy variables, political incentives related to crime and violence may move in the opposite direction to what this literature predicts.

Second, crime can change rapidly as compared to other economic policy variables that move slowly. So unlike a change in infrastructure projects (as in Khemani

[46]Rogoff and Sibert (1988) first studied electoral cycles with rational voters and office-motivated politicians, who cared both about winning and voters' welfare, in the presence of exogenous rents and adverse selection problems. Rogoff (1990) generalized these results to two-dimensional signalling by the incumbent. Previously, Nordhaus (1975) and Lindbeck (1976) found political business cycles using the assumption that voters are irrational and backward-looking in their economic and voting decisions. Electoral cycles are consistent with a wide variety of models, including those with adverse selection and moral hazard, office-motivated and partisan politicians (Alesina, 1988; Alesina, 1987) as well as partisan parties that differ in ability (Alesina et al., 1995; Alesina et al., 1993).

(2004)), which is rightly attributed to a change in political performance, in the case of crime, the decline in crime only occurs very close to the election period. During this time, it is the EC which is in control of the local administration and police. Hence, unlike other economic variables, voters may not attribute the decrease in crime to politicians. Further, electoral motives can explain why riots increase, but they cannot explain why instances of traffic violations increase and cases of domestic violence decrease, since perpetrators in this context are unlikely to be political agents.

However, without further evidence on the targeting of preventive action or on the impact of prevention and enforcement on political outcomes, I cannot rule out the role of politicians and criminals. The increase in preventive action and the suggested changes in the nature of enforcement are consistent with political incentives for re-election. Reduced individual crimes can help politicians look more competent before elections, and higher levels of strategic electoral violence in the form of higher public order-related events could increase coercion, both of which could increase the likelihood of re-election. My qualitative work reflects the low likelihood of the role of politicians in reducing individual crime – not a single police official, EC official, or even politician mentioned the role of political performance and the desire to decrease crime.[47] If anything, they mentioned the role of 'other' politicians and general political activity in inciting violence during campaigns. However, this does not rule out the possibility of collaboration of politicians with the police to increase prevention and change the nature of enforcement.

[47]One of the interviewees, who had been part of several political campaigns, said "Once the MCC [Model Code of Conduct] is applied, ... politicians have less power, the administration has more power. There are officers who are quite strict, so they get hold of the illegal liquor, money being transported across cities, borders." (P75)

Table 2.12: Alternative Mechanisms

Prediction of Literature	**Electoral Cycles**	**Electoral Violence**	**This Paper**
Preventive Action	Increase	*[None]*	Increase
Crimes against Public Order	*[Decrease]*	Increase	Increase
Other Crimes	Decrease	*[None]*	Decrease
Mechanisms	Strategic incentives of politicians to *reduce* violence	Strategic incentives of politicians to *increase* violence	Police behaviour (prevention, enforcement) driven by (i) career concerns, multitasking, or (ii) by political incentives

Notes: Predictions made within square brackets refer to predictions that are not explicitly discussed in the literature.

2.6.1 Role of the Election Commission

Qualitative evidence suggests that the temporary change in the structure of government during the election period has some implications for the behaviour of the prevention and enforcement behaviour of the police. Since the police is under the purview of the EC for the election period, this entails a change in the supervisory structure and the relationships between local politicians and local bureaucrats, even if for a short period. Bureaucrats cannot be certain of who will be in power once the election is complete. Within the election period though, it is the EC that is responsible for all personnel decisions. Officers are routinely transferred where there are concerns about the neutrality of the officer (Quraishi, 2014) and career concerns are in play as the EC provides a performance evaluation for officers that has implications for future postings as election observers, as mentioned by several interviewees.

The emphasis at this time on the role of preventive action, which is an instrument that is available to the police at all times, comes from the guidance of the EC (Election Commission of India, 2014). A daily 'Law & Order Report' for each district is prepared in a given format and is submitted by the police from the announcement of

elections onwards until the completion of elections. In addition to this, fortnightly information on the implementation of the special drives at the constituency level is prepared (Election Commission of India, 2014). The number of bind overs done seems to be an important metric, among others, of the performance of the police in the view of the EC, and is reported daily to the EC through the Chief Electoral Officer. Even though there are mixed views within the police regarding the effectiveness of the preventive activity, officers continue to undertake such action because of the role of the EC in personnel management, especially in influencing transfers and career records during the election period, as can be seen from some of the interviews below.[48]

When asked about what the performance metrics for the police during elections are, a junior officer said,

"I would actually say that the binding down that takes place at this time becomes a competitive binding down. There is target in some sense based on the binding over that was done in the previous election. If last time there were 10,000 people bound down, then this time I will try to do 10,000+x. So if I am a SP, I will tend to go overboard to show my superiors. That is an intra-district comparison. There will also be other comparisons. So within a range, which is comprised of 3-4 districts, I will try to bind over the most number of people. Even if this is unrelated, and if it might not help, but if something goes wrong, then at least the superiors will not say that no measures were taken. The amount of cash seized, the number of drives implemented, the number of tickets given to motor vehicles violations, the amount of liquor seized, etc. will all be quite important. So actually we are quite indiscriminate and ruthless with binding over in a way that does not happen in a democracy at any time except around elections." (P75)

He continued,

"This has important career implications as well, since the Election Commission can make an 'adverse note' on conduct in the service record if the person is not seen as being fully active. And unlike the state government, the EC does not easily condone

[48]Meloni (2018) observes that the short-term actions of the government close to elections and their crime prevention efforts "do not aim to alter the roots of crime; they are just intended to reduce crime in the short term." In this paper, the incentives of the EC and the police are likely similar – locking up large numbers of individuals is unlikely to reduce crime in the long run, and might not do so in the short run either. But if the right individuals are locked up, the elections may go off without major hitches.

these notes. The consequence is that the individual will not be deployed on election duty again. So we go overboard. We are not sure what to do, so we do everything. We make sure there are a large number of bonds being issued, binding down, etc." (P75)

Other officers agreed both on the performance target in terms of preventive action and the threat of transfers. "Preventive action is a performance metric, I would say. 'How many' matters a lot. The number of preventive actions and bind overs is definitely a performance metric. ... The numbers matter. If you say numbers, they will show numbers." (P51) "As the DM [District Magistrate], I'm directly responsible and answerable to the Election Commission. During elections, the CM [Chief Minister], the state administration no longer matters. You report to the EC, through the CEO [Chief Electoral Officer]. And they can transfer officers overnight. To be removed during an election is considered very poorly. It's okay if you are removed from your post at any other time, but if you are removed during election times, it is like a blot on your career. It stays forever." (P71)

In addition to these, some other observations about the performance metrics for the police and the role of the EC can be found in Appendix 2.B. Together, these comments provide an insight into the changes in preventive activity and enforcement that can be seen in the quantitative analysis.

2.7 Conclusion

This paper studies the impact of election timing on crime and the nature of law enforcement in a developing country known for electoral violence. I use administrative crime data, data on political violence from ACLED, as well as qualitative data from interviews conducted with elite and frontline officials in India to provide evidence for the existence of electoral cycles in crime. I show that elections have a mixed impact on crime – increasing crimes against public order while reducing other crimes against individuals, such as those related to bodily offences, property,

or women. Qualitative work suggests that a part of this change in crimes can be explained by changes in the enforcement of crime by police, who reduce the enforcement of certain crimes against individuals, even as they increase the enforcement of crimes against public order.

This paper also examines the role of preventive tools that can be used by law enforcement agencies. I show that preventive activity increases sharply as elections approach. These changes in prevention and enforcement are consistent with multitasking by bureaucrats as well as the re-election incentives of politicians. Future research can help us understand the alternative roles of bureaucrats and politicians in this setting. I plan to study the relationship between prevention and enforcement by the police and political outcomes – for example, is the police more or less responsive to the demands of the Election Commission in constituencies with different political characteristics, such as incumbency and political alignment. Similarly, to understand the role of multitasking, it would be useful to study whether concomitant changes in prevention and enforcement are taking place in the same police stations and if there are any differences in the utilization of resources by the police at this time.

This paper contributes to the literature on optimal policing in developing countries and provides some of the most detailed descriptive and causal evidence of the impact of election timing on crime in this setting. However, several questions remain. In the context of crime, we need to further understand the targeting and effectiveness of preventive action. In its current form, not a lot is known about who is 'bound over' using the preventive sections of the Criminal Procedure Code, or what their criminal or political background is. We also do not know the 'impact' of preventive activity in terms of how much it reduces crime, or if it does so at all, and its overall impact on citizen welfare. Finally, understanding the effectiveness of preventive activity would also help us understand whether prevention and enforcement are complements or substitutes, which has important implications for the optimal allocation of policing

resources. This constitutes an important area of future work in understanding the interactions between politicians, bureaucrats, and law enforcement in the context of crime and political violence.

More broadly, elections represent a composite treatment, where several political, criminal, and administrative features change simultaneously. Future work could help to disentangle the role of each of these features and how they independently affect crime. Future work could also specifically look at the role of local elections on crime, as local elections differ in terms of EC control, and are known to be more violent than state elections. Our understanding of crime, electoral violence, and the optimal use of policing resources is hindered by the lack of systematic data made available on the deployment of the police, complaints of electoral violence received by the Election Commission, and investigations of electoral crimes by the police (Verma, 2005). Adopting a standardized approach for classifying election-related crimes and improving data quality and completeness in police departments, for example, on the motives of crime, would go a long way in contributing to the rigorous and evidence-based study of crime, and policing in developing countries.

References

Ahuja, Amit and Susan L. Ostermann, "From Quiescent Bureaucracy to "Undocumented Wonder": Explaining the Indian Election Commission's Expanding Mandate," *Governance*, October 2018, *31* (4), 759–776.

Alesina, Alberto, "Macroeconomic Policy in a Two-Party System as a Repeated Game," *Quarterly Journal of Economics*, 1987, *102* (3), 651–678.

_ , "Credibility and Policy Convergence in a Two-Party System with Rational Voters," *The American Economic Review*, 1988, *78* (4), 796–805.

_ **and Guido Tabellini**, "Bureaucrats or politicians? Part II: Multiple policy tasks," *Journal of Public Economics*, April 2008, *92* (3), 426–447.

_ **and Howard Rosenthal**, *Partisan Politics, Divided Government, and the Economy* Political Economy of Institutions and Decisions, Cambridge: Cambridge University Press, 1995.

_ **, John Londregan, and Howard Rosenthal**, "A Model of the Political Economy of the United States," *The American Political Science Review (1927)*, 1993, *87* (1), 12–33.

Association for Democratic Reforms, "Criteria for Categorization of Serious Criminal Cases," 2014.

Banerjee, Abhijit, Esther Duflo, Daniel Keniston, and Nina Singh, "The Efficient Deployment of Police Resources: Theory and New Evidence from a Randomized Drunk Driving Crackdown in India," *National Bureau of Economic Research Working Paper 26224*, September 2019.

_ **, Raghabendra Chattopadhyay, Esther Duflo, Daniel Keniston, and Nina Singh**, "Improving Police Performance in Rajasthan, India: Experimental

Evidence on Incentives, Managerial Autonomy, and Training," *American Economic Journal: Economic Policy*, February 2021, *13* (1), 36–66.

Berdejó, Carlos and Noam Yuchtman, "Crime, Punishment, and Politics: An Analysis of Political Cycles in Criminal Sentencing," *Review of Economics and Statistics*, 2013, *95* (3), 741–756.

Berenschot, Ward, "On the Usefulness of Goondas in Indian Politics: 'Money-power' and 'Musclepower' in a Gujarati Locality," *South Asia: Journal of South Asian Studies*, August 2011, *34* (2), 255–275.

_ , "Patterned pogroms: Patronage networks as infrastructure for electoral violence in India and Indonesia," *Journal of Peace Research*, January 2020, *57* (1), 171–184.

Besley, Timothy and Robin Burgess, "The Political Economy of Government Responsiveness: Theory and Evidence from India," *Quarterly Journal of Economics*, 2002, *117* (4), 1415–1451.

Birch, Sarah and David Muchlinski, "Electoral Violence Prevention: What Works?," *Democratization*, April 2018, *25* (3), 385–403.

_ **, Ursula Daxecker, and Kristine Höglund**, "Electoral violence: An introduction," *Journal of Peace Research*, January 2020, *57* (1), 3–14.

Burbidge, John B., Lonnie Magee, and A. Leslie Robb, "Alternative Transformations to Handle Extreme Values of the Dependent Variable," *Journal of the American Statistical Association*, 1988, *83* (401), 123–127.

Chalfin, Aaron and Justin McCrary, "Criminal Deterrence: A Review of the Literature," *Journal of Economic Literature*, March 2017, *55* (1), 5–48.

Chandra, Kanchan, *Why Ethnic Parties Succeed: Patronage and Ethnic Head Counts in India* Cambridge Studies in Comparative Politics, Cambridge: Cambridge University Press, 2004.

Chowdhury, Shreya Roy, "The Silent Army: Behind India's election are 5 million workers.," *Scroll.in*, April 2019.

Dar, Aaditya, Pranav Gupta, and Rahul Verma, "Electoral Cycles in Food Prices: Evidence from India," October 2018.

Daxecker, Ursula, "Unequal votes, unequal violence: Malapportionment and election violence in India," *Journal of Peace Research*, January 2020, *57* (1), 156–170.

de Chaisemartin, Clément and Xavier D'Haultfœuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *The American Economic Review*, 2020, *110* (9), 2964–2996.

Dewatripont, Mathias, Ian Jewitt, and Jean Tirole, "The Economics of Career Concerns, Part II: Application to Missions and Accountability of Government Agencies," *Review of Economic Studies*, January 1999, *66* (1), 199–217.

Draca, M., S. Machin, and R. Witt, "Panic on the Streets of London: Police, Crime, and the July 2005 Terror Attacks," *American Economic Review*, 2011, *101* (5), 2157–2181.

Election Commission of India, "Check List for Police Officers: General Elections 2014," 2014.

Ghosh, Arkadipta, "Electoral Cycles in Crime in a Developing Country: Evidence from the Indian States," SSRN Scholarly Paper ID 910054, Social Science Research Network, Rochester, NY June 2006.

Gilmartin, David and Robert Moog, "Introduction to "Election Law in India"," *Election Law Journal: Rules, Politics, and Policy*, June 2012, *11* (2), 136–148.

Hafner-Burton, Emilie M., Susan D. Hyde, and Ryan S. Jablonski, "Surviving Elections: Election Violence, Incumbent Victory and Post-Election Repercussions," *British Journal of Political Science*, April 2018, *48* (2), 459–488.

Harish, S. P. and Andrew T. Little, "The Political Violence Cycle," *American Political Science Review*, May 2017, *111* (2), 237–255.

Hendrix, Cullen S. and Idean Salehyan, "No News Is Good News: Mark and Recapture for Event Data When Reporting Probabilities Are Less Than One," *International interactions*, 2015, *41* (2), 392–406.

Holland, Alisha, "Forbearance," *The American Political Science Review*, 2016, *110* (2), 232–246.

Holmstrom, Bengt and Paul Milgrom, "Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design," *Journal of Law, Economics, & Organization*, 1991, *7* (Special Issue: [Papers from the Conference on the New Science of Organization, January 1991]), 24–52.

Höglund, Kristine, "Electoral Violence in Conflict-Ridden Societies: Concepts, Causes, and Consequences," *Terrorism and Political Violence*, June 2009, *21* (3), 412–427.

III, John J. Donohue and Steven D. Levitt, "The Impact of Race on Policing and Arrests," *The Journal of Law & Economics*, 2001, *44* (2), 367–394.

Imai, Kosuke and In Song Kim, "On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data," *Political Analysis*, July 2021, *29* (3), 405–415. Publisher: Cambridge University Press.

Iyer, Lakshmi, Anandi Mani, Prachi Mishra, and Petia Topalova, "The Power of Political Voice: Women's Political Representation and Crime in India," *American Economic Journal: Applied Economics*, 2012, *4* (4), 165–193.

Johari, Aarefa, "How free and fair are the world's biggest elections?," *Scroll.in*, April 2014.

Khemani, Stuti, "Political cycles in a developing economy: effect of elections in the Indian States," *Journal of Development Economics*, 2004, *73* (1), 125–154.

Labonne, Julien, "Local Political Business Cycles: Evidence from Philippine Municipalities," *Journal of Development Economics*, 2016, *121*, 56–62.

Levitt, Steven, "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime," *The American Economic Review*, June 1997, *87* (3), 270–290.

Lindbeck, Assar, "Stabilization Policy in Open Economies with Endogenous Politicians," *The American Economic Review*, 1976, *66* (2), 1–19.

Mani, Anandi and Sharun Mukand, "Democracy, visibility and public good provision," *Journal of Development Economics*, July 2007, *83* (2), 506–529.

Meloni, Osvaldo, "Is there an electorally-motivated crime rate cycle? Evidence from Argentina," *Economics Bulletin*, 2018, *38* (2), 1102–1111.

Mendiratta, S.K., "Interview by Michael Scharff," November 2010.

Nath, Suman, "Party-people and local governance in an Indian state: a longitudinal study on the roots of electoral violence," *India Review*, May 2020, *19* (3), 280–300.

Nordhaus, W., "The Political Business Cycle," *The Review of Economic Studies*, 1975, *42* (2), 169–190.

Oberg, Magnus and Margareta Sollenberg, "Gathering conflict information using news resources.," in Kristine Hoglund and Magnus Oberg, eds., *Understanding Peace Research: Methods and Challenges*, London: Taylor & Francis Group, 2011, pp. 47–73.

Pierskalla, J. H. and A. Sacks, "Personnel Politics: Elections, Clientelistic Competition and Teacher Hiring in Indonesia," *British Journal of Political Science*, 2019.

Pollmann, Daniela and Kunal Purohit, "Securing Democracy: Electoral Violence in India. The Armed Conflict Location & Event Data Project," April 2019.

Prendergast, Canice, "Selection and Oversight in the Public Sector, With the Los Angeles Police Department as an Example," *National Bureau of Economic Research Working Paper 8664*, December 2001.

Press Trust of India, "Over 3 lakh paramilitary, 20 lakh state police personnel were deployed for 7-phase Lok Sabha polls," *India Today*, May 2019.

Quraishi, S. Y., *An Undocumented Wonder: The Great Indian Election*, New Delhi: Rainlight, Rupa Publications, 2014.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen, "Introducing ACLED-Armed Conflict Location and Event Data," *Journal of Peace Research*, 2010, *47* (5), 651–660.

Rogoff, Kenneth, "Equilibrium Political Budget Cycles," *The American Economic Review*, 1990, *80* (1), 21.

_ **and Anne Sibert**, "Elections and Macroeconomic Policy Cycles," *The Review of Economic Studies*, 1988, *55* (1), 1–16.

Shukla, Alok, "Interview by Michael Scharff," November 2010.

Smidt, Hannah, "Mitigating election violence locally: UN peacekeepers' election-education campaigns in Côte d'Ivoire," *Journal of Peace Research*, January 2020, *57* (1), 199–216.

Staniland, Paul, "Violence and Democracy," *Comparative Politics*, October 2014, *47* (1), 99–118.

Suri, Manveena and Swati Gupta, "India Election 2019: The Key Statistics," March 2019.

Taylor, Charles, "Shared Security, Shared Elections: Best Practices for the Prevention of Electoral Violence," Technical Report, American Friends Service Committee 2018.

Tella, Rafael Di and Ernesto Schargrodsky, "Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack," *American Economic Review*, 2004, *94* (1), 115–133.

Tellez, Juan Fernando, Erik Wibbels, and Anirudh Krishna, "Local Order, Policing, and Bribes: Evidence from India," *World Politics*, July 2020, *72* (3), 377–410. Publisher: Cambridge University Press.

Verma, Arvind, "Policing Elections in India," *India Review*, July 2005, *4* (3-4), 354–376.

von Borzyskowski, Inken and Michael Wahman, "Systematic Measurement Error in Election Violence Data: Causes and Consequences," *British Journal of Political Science*, January 2021, *51* (1), 230–252.

Weidmann, Nils B., "A Closer Look at Reporting Bias in Conflict Event Data," *American Journal of Political Science*, 2016, *60* (1), 206–218. Place: Hoboken Publisher: Blackwell Publishing Ltd.

Wilkinson, Steven, *Votes and Violence: Electoral Competition and Ethnic Riots in India* Cambridge Studies in Comparative Politics, Cambridge: Cambridge University Press, 2004.

Wilson, James Q., *Varieties of Police Behavior: The Management of Law and Order in Eight Communities*, Cambridge, MA: Harvard University Press, 1978.

_ **and George L. Kelling**, "Broken Windows: The Police and Neighborhood Safety," *Atlantic Monthly*, 1982, *249* (3), 29–38.

Appendix

2.A Methodology for Qualitative Interviews

Anonymous, qualitative interviews with elite officials in India were conducted as a part of this research to understand the context and the mechanisms driving the results in much greater depth. This study has been reviewed by, and received ethics clearance through, the University of Oxford Central University Research Ethics Committee (Reference number: SSH/BSG-C1A-20-31).

2.A.1 Sample

I conducted interviews with individuals selected on the basis of purposive sampling and snowballing. There were three groups of people who were interviewed. First: officials who currently work or previously worked in policy-making and implementation positions at the Election Commission of India, or any of the State Election Commissions across the country, including officials who served as election observers. Second: police officials posted in the central government or in state governments who take part in the implementation of security arrangements at the time of elections. This included relatively senior officials posted in government offices as well as officials who are the heads of police stations, and different levels in between. Third: politicians at the central, state or local levels who have previously contested elections or are in office, or their campaign managers. I interviewed a total of 15 individuals. Of these, 2 had worked in the Election Commission of India or served as election observers. 3 were police officers with over 25 years of experience, 4 were police officers of the SP or SSP rank, with 9-15 years of experience. These individuals have served in the field in the recent past. 2 officers were heads of police stations. 1 was an administrative service officer. 3 interviewees had experience working on

or leading major political campaigns in the country. The average duration of an interview was 45.27 minutes. All interviewees were 18 years of age or older.

2.A.2 Methodology

The interviews for the study were conducted online, or over a phone call. I obtained oral consent for all interviewees, interviews were not recorded. I took hand-written notes. While research data was collected, no personal data of sensitive nature/special category data was collected. All research data collected has been securely encrypted and stored. Most of the interviews were conducted entirely in English. A few interviews were conducted in a mix of English and Hindi. As I am fully proficient in Hindi, I was be able to conduct the interviews and transcribe them myself. I have translated the material into English for the purpose of presentation and inclusion in this paper. Where there are certain nuances or ambiguities, I have also included the original Hindi phrase.

Where elite interviewees could be identified from their position, location, or other contextual information, I have omitted or anonymized the information (for example, name of district) to ensure that the individual cannot be identified. In most cases, this was not an issue as there are multiple officials working in a state or district. I have ensured that an individual cannot be re-identified through contextual information. No names or other identifying details of interviewees have been used in this paper. I have pseudonymized all interviewees with two-digit codes of the form 'Pxx', where 'P' refers to 'participant', and 'xx' is a randomly-generated two-digit number. I wrote up the transcripts within 2 hours of the interview and have tried to stick as closely as possible to what the interviewee said verbatim, but in some cases, for clarity and to fill gaps, the sentences are close paraphrases. For clarity, I present all the qualitative material collected in quotation marks, but some of these are exact quotes and others are close paraphrases.

2.B Additional Observations on Performance Metrics and Transfers

P60: The police do take some steps to safeguard themselves, so that they can tell the EC that they are doing things. The number of arrests (preventive) would increase, so they might just pick anyone off the streets. In cases where the police is much more hand in glove with politicians – there is a full spectrum of the police themselves – in that case, they would pick up the goons of the opposite party and give them a lot of serious cases.

P51: Preventive action is a performance metric, I would say. 'How many' matters a lot. The number of preventive actions and bind overs is definitely a performance metric. But then a second aspect of it is the quality of it. The numbers matter. If you say numbers, they will show numbers. But other than that you also need to ensure quality of the preventive action. You need to check have all the rowdy sheeters been taken in? Look at the seizure of cash, liquor. This will tell us about enforcement. When I say quality of procedure, I mean are we following the procedure that is laid out in the CrPC. When we focus on numbers, quality might take a backseat. But there are two aspects of quality – who is being booked over, and are we following the right procedure?

P36: The system of evaluating whether any individual is doing their job is the checklist – there is a daily checklist, then there is a weekly checklist, then there is a fortnightly checklist, and so on. So whether someone is performing or not, we get to know through that evaluation system. Yes, these checklists will contain information such as the number of bind over cases, the execution of non-bailable warrants, the number of arms surrendered, etc. The checklist also includes information on election related offences from previous elections. What happens is that everyone usually forgets about election-related offences as soon as the election is done. So when

a new election approaches, we also take out information on election offences from the previous time, how were they dealt with, and then action begins – quickly chargesheets are filed, offenders are caught, they seek bail, and so on.

P99: To keep track of the cases related to elections, we pay special attention to cases related to elections, or other such cases, we treat them as special crimes, treat them as 'more than normal' crimes. We keep track of such cases, as they are quite important for public order. For example, cases that were registered during previous elections, when the next election comes, the EC wants to know. There are periodic reviews of such cases, for example, 6 month or 1 year reviews, and the DGP Office asks for the progress report. So a little more attention is paid to these cases, cases relating to public order. It is in our own interest to pay extra attention to these cases, since they are cases related to public order, and it can lead to a lot of criticism if not dealt with. But yes, also these cases are reviewed at the time of future elections, so EC monitoring matters.

P36: The police is more active as in a way they are under a single chain of command under the ECI now, and they know that they will be held accountable for whatever happens in their areas, and there is no kind of extraneous *mai-baap* available to them during this period.

P75: Since the Election Commission takes control of the administrative and supervision powers at this time, there is an incentive to defer cases.

2.C Difference-in-Differences Analysis

In this appendix, I further aim to establish causal impact using a difference-in-differences analysis for the states of Andhra Pradesh (AP) and Telangana (TS), by presenting additional evidence that the results are not merely driven by time trends which may be correlated with state-wise election timing.[49]

2.C.1 Difference-in-Differences Design

The states of AP and TS held three elections each over the sample period - 2009, 2014 and 2018/2019. In the elections of 2009 and 2014, the two states together formed a single, larger state (also called 'Andhra Pradesh'). The state of Telangana was separated out from the larger state in mid-2014. The new state did not follow the old election cycle, under which elections would have taken place in May 2019, and declared early elections, to be held in December 2018. As a result, the two states have different election cycles in the 2018-19 period. I use this to undertake a difference-in-differences analysis. I define AP as 1 in the period before the separation of the two states, as well as for the part of the old state that is still called AP at present. The new state of Telangana in the post-separation period takes the value AP=0.

In the section below, I estimate regressions of the following form.

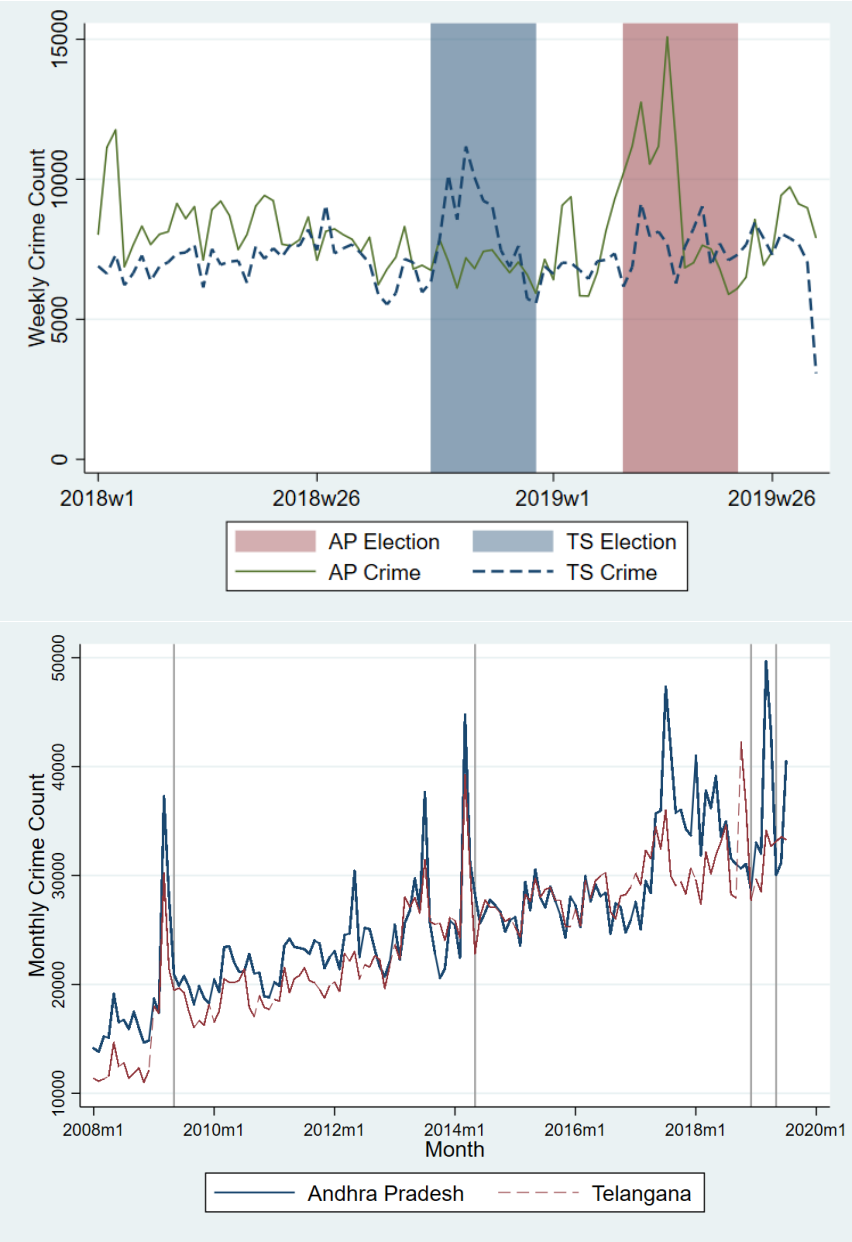
$$Crime_{it} = \beta_0 + \beta_1 AP_i + \beta_2 AP_i * Election_t + \beta_3 TS_i * Election_t + \alpha_i + \gamma_t + \epsilon_{it} \quad \text{(B.2)}$$

The first panel of Figure 2.C.1 presents the weekly trends in crime in the states of AP and TS over the 2018-2019 when their election cycles diverged. As can be seen, the crime trends are parallel, except in the shaded periods, which are election periods

[49] When a state no longer has an election at a given time, there are no other trends that lead to changes in crime during that period.

for Telangana and AP, respectively. The second panel of the figure presents the longer term monthly trends in crime for the two states, which also move together.

Figure 2.C.1: Parallel Trends Hold for States of Andhra Pradesh and Telangana



Notes: These figures show the trends in crime in the states of Andhra Pradesh and Telangana. (i) The first panel presents weekly totals of crime count in the Jan 2018- July 2019 period when the election cycles of the two states diverged. (ii) The second panel presents monthly totals over the 2008-2019 period and shows that crime patterns in the two states are similar. In the second panel, the vertical lines represent election months. In 2009 and 2014, both AP and TS held elections at the same time. TS held its subsequent elections earlier, in 2018, whereas AP continued to follow the previous 5-year cycle and held elections in 2019.

2.C.2 Difference-in-Differences Results

This section presents the main results from the difference-in-differences analysis described above. Table 2.C.1 shows the main results using the DiD specification. The DiD results for the overall cases, violations count, non-penal code count, and election crimes remain consistent with previous results. In the case of crimes and serious crimes registered on the Indian Penal Code, however, the DiD coefficients for Andhra Pradesh are not significantly different from zero, indicating differences in the police strategies of enforcement as compared to prevention among the two states. Table 2.C.2 shows the results for the preventive sections using the DiD specification. Consistent with previous results, the DiD estimators are positive and significant.

Table 2.C.1: DiD: Impact of Election Periods on Daily Crime in Full Dataset

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious Crime	(6) Election
State=AP	-0.0244***	-0.0413***	-0.0477***	0.00217	-0.0329***	-0.000179**
	(0.006)	(0.008)	(0.006)	(0.004)	(0.004)	(0.000)
AP*Election	0.0529***	0.0462***	-0.00240	0.0558***	-0.00100	0.0278***
	(0.005)	(0.007)	(0.006)	(0.005)	(0.004)	(0.001)
TS*Election	0.190***	0.197***	0.0215***	0.209***	0.00765*	0.0143***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.005)	(0.001)
Constant	0.356***	0.498***	0.385***	0.174***	0.242***	0.0000158
	(0.005)	(0.006)	(0.005)	(0.004)	(0.003)	(0.000)
PS FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7781212	7781212	7781212	7781212	7781212	7781212

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents difference-in-differences regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the full dataset of all police stations in the states of Andhra Pradesh and Telangana. The dependent variable in Columns 1-6 refers to the number of police complaints filed, the number of criminal violations, the number of IPC violations, the number of non-IPC violations, the number of serious IPC violations (as defined by ADR (2014)), and the number of electoral violations under Chapter IXA of the IPC, respectively. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

Table 2.C.2: DiD: Impact of Election Periods on Daily Preventive Activity

	(1) CrPC Count
State=AP	-0.000833
	(0.002)
AP*Election	0.137***
	(0.002)
TS*Election	0.214***
	(0.006)
Constant	0.0821***
	(0.001)
Police Station FE	Yes
Year FE	Yes
Week FE	Yes
Observations	7377193

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents difference-in-differences regression estimates of the impact of being in an election period on the count of CrPC crimes at the daily-police station level using the full dataset of all police stations in the states of Andhra Pradesh and Telangana. The dependent variable is transformed using the inverse hyperbolic sine transformation. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

Table 2.C.3 shows the results from the DiD analysis for the impact of elections on murders. While the DiD estimate for AP is significant, the DiD estimate for Telangana state is not statistically significant, indicating that there is no change in the underlying level of murders (actual or reported) in the state during the election period. Again, this may indicate differences in underlying patterns of prevention and enforcement in the two states.

Table 2.C.3: DiD: Impact of State Election Periods on Daily Murder Count

	(1) Murder Count
State=Andhra Pradesh	0.000344***
	(0.000)
AP*Election Period	-0.000583***
	(0.000)
TS*Election Period	-0.000211
	(0.000)
Constant	0.00322***
	(0.000)
Police Station FE	Yes
Year FE	Yes
Week FE	Yes
Observations	6890462

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents difference-in-differences regression estimates of the impact of being in an election period on murders at the daily-police station level using the full dataset of all police stations in the states of Andhra Pradesh and Telangana. The dependent variable is transformed using the inverse hyperbolic sine transformation. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

2.D Robustness Checks

2.D.1 Results are Consistent in using the Partial Dataset

All versions of the results so far use the full dataset (56 million observations), which includes all police stations from the crime data, even if they cannot necessarily be mapped to a constituency. Using the full dataset has the advantage that it includes (a) states that do not have a police station-constituency mapping, and (b) crime recorded in split police stations can be included even when a PS cannot be uniquely mapped to an AC. However, the analysis using by-elections requires constituency-level information, as elections in these cases are not a state-wide treatment but are determined at the constituency level. To derive these results, I use a partial dataset of 30 million observations, where each police station had a constituency mapping. Before doing so, I show that the main results hold in the partial dataset (Tables 2.D.4, 2.D.5), suggesting that the effects in the analysis of by-elections are not being driven by merely changes in the sample. Standard errors in the full dataset are clustered at the police station level and in the partial dataset are clustered at the assembly constituency level, which is the most strict choice of cluster in either of the cases.

Table 2.D.4: Impact of Election Periods on Daily Crime in the Partial Dataset

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious Crime	(6) Election
Election	0.0814***	0.0845***	-0.00623***	0.110***	-0.00792***	0.00968***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.000)
Constant	0.435***	0.626***	0.477***	0.236***	0.271***	0.000242***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PS FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30696004	30696004	30696004	30696004	30016164	30016164

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the partial dataset of police stations, that is, police stations that can be mapped uniquely to assembly constituencies. The dependent variable in Columns 1-6 refers to the number of police complaints filed, the number of criminal violations, the number of IPC violations, the number of non-IPC violations, the number of serious IPC violations (as defined by ADR (2014)), and the number of electoral violations under Chapter IXA of the IPC, respectively. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Columns 5 and 6 do not include data from the erstwhile state of Jammu and Kashmir as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the assembly constituency level. No other covariates are included.

Table 2.D.5: DiD: Impact of Election Periods on Daily Crime in the Partial Dataset

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious Crime	(6) Election
State=AP	-0.0163**	-0.0365***	-0.0449***	0.00888	-0.0322***	-0.000229
	(0.007)	(0.010)	(0.008)	(0.007)	(0.005)	(0.000)
AP*Election	0.0727***	0.0733***	0.00689	0.0791***	-0.00118	0.0320***
	(0.009)	(0.011)	(0.009)	(0.009)	(0.002)	(0.002)
TS*Election	0.212***	0.209***	0.0155	0.227***	0.00598	0.0155***
	(0.013)	(0.016)	(0.010)	(0.013)	(0.004)	(0.002)
Constant	0.352***	0.503***	0.389***	0.167***	0.241***	0.000000551
	(0.006)	(0.008)	(0.006)	(0.006)	(0.004)	(0.000)
PS FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5696896	5696896	5696896	5696896	5696896	5696896

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents difference-in-differences regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the partial dataset of all police stations in the states of Andhra Pradesh and Telangana that can be uniquely mapped to an assembly constituency. The dependent variable in Columns 1-6 refers to the number of police complaints filed, the number of criminal violations, the number of IPC violations, the number of non-IPC violations, the number of serious IPC violations (as defined by ADR (2014)), and the number of electoral violations under Chapter IXA of the IPC, respectively. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the assembly constituency level. No other covariates are included.

2.D.2 Results not Driven by Time Trends

2.D.2.1 By-elections Analysis with Detailed Time Trends

The main results shown so far might be capturing overall time trends, either at the national or at the state level. I take advantage of by-elections to rule this out. All results for by-elections use the partial dataset since by-elections are declared and conducted at the constituency level. I use the same regression specification as before, but including all by-elections as well in the sample of state elections. Police station fixed effects and State*Week*Year FE are included. The much finer time fixed effects in this analysis allow me to rule out issues of time trends within states. Results are shown in Table 2.D.6. As can be seen, the results are consistent with the main results in the paper, with the exception of IPC and IPC serious crime, which are not significant. This may point towards differences in enforcement behaviour in state elections and by-elections.

Table 2.D.6: Impact of Election Periods on Daily Crime using By-Elections

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious Crime	(6) Election
By Election Period	0.0650***	0.0670***	-0.00743	0.0857***	-0.00986	0.0106***
	(0.016)	(0.016)	(0.011)	(0.013)	(0.007)	(0.002)
Regular Election Period	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
Constant	0.438***	0.629***	0.477***	0.240***	0.271***	0.000586***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30696004	30696004	30696004	30696004	30016164	30016164

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the partial dataset of all police stations that can be mapped to a unique constituency. The dependent variable in Columns 1-6 refers to the number of police complaints filed, the number of criminal violations, the number of IPC violations, the number of non-IPC violations, the number of serious IPC violations (as defined by ADR (2014)), and the number of electoral violations under Chapter IXA of the IPC, respectively. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Columns 5 and 6 do not include data from the erstwhile state of Jammu and Kashmir as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique state-week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the assembly constituency level. No other covariates are included.

2.D.2.2 Similarity between places with and without by-elections

Further, I rule out the possibility that there is something different about the constituencies where by-elections take place. I am already controlling for constant differences in crime using police station fixed effects. To control for any underlying differences that kick in during the specific by-election periods, for example, if the by-election itself is the result of high levels of violence or death of the incumbent, I include the indicator variable $ByElection_{it}$, which takes the value 1 if constituency i has a by-election at any point in a given assembly period. The variable $ByElectionPeriod_{it}$ takes the value 1 if there is a by-election period on a given day t in constituency i. $RegularElectionPeriod_{ist}$ takes the value 1 if there is a regular-election period on a given day t in constituency i.[50] The sample includes all constituencies regardless of whether they have a by-election at some point. The results of this analysis can be seen in Table 2.D.7.

[50]There are some cases where $ByElection_{it}$ changes within State*Week*Year, when the election process begins mid-week. Similarly, $StateByElectionPeriod_{it}$ and $RegularElectionPeriod_{ist}$ also change mid-week. I have redefined these three variables such that they take the value 1 if the election process begins anytime during a given week.

Table 2.D.7: Impact of Election Periods on Daily Crime using By-Elections II

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious Crime	(6) Election
By Election Period	0.0666***	0.0678***	-0.00515	0.0855***	-0.00859	0.0106***
	(0.015)	(0.015)	(0.009)	(0.013)	(0.005)	(0.002)
Regular Election Period	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
By Election	-0.00285	-0.00151	-0.00410	0.000406	-0.00228	0.000170
	(0.008)	(0.010)	(0.008)	(0.008)	(0.006)	(0.000)
Constant	0.438***	0.629***	0.477***	0.240***	0.271***	0.000578***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30696004	30696004	30696004	30696004	30016164	30016164

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

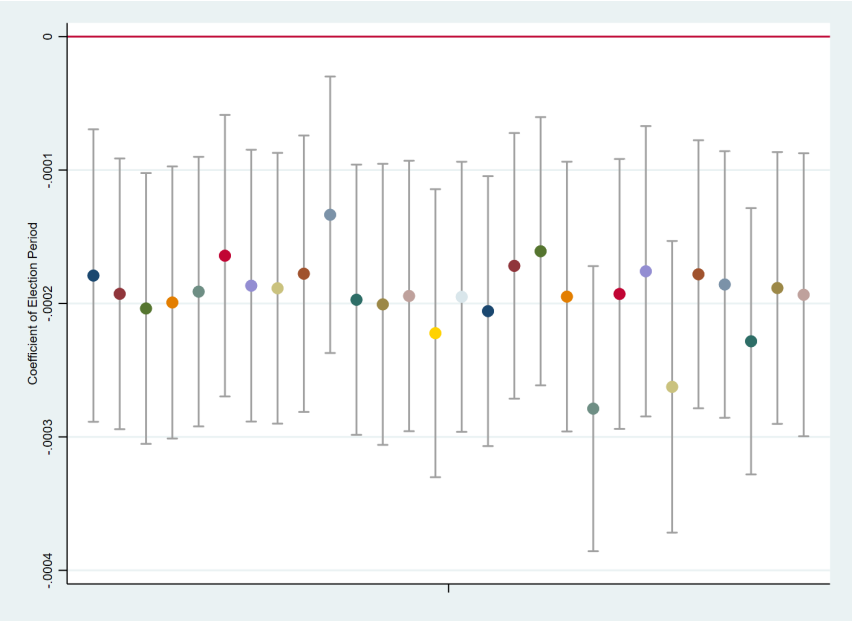
Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the partial dataset of all police stations that can be mapped to a unique constituency. The dependent variable in Columns 1-6 refers to the number of police complaints filed, the number of criminal violations, the number of IPC violations, the number of non-IPC violations, the number of serious IPC violations (as defined by ADR (2014)), and the number of electoral violations under Chapter IXA of the IPC, respectively. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Columns 5 and 6 do not include data from the erstwhile state of Jammu and Kashmir as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique state-week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the assembly constituency level. No other covariates are included.

2.D.3 Results not Driven by Any State

2.D.3.1 Robustness to the inclusion of different states

Results are robust to the sample in terms of the states included. Figure 2.D.2 shows the change in murder counts during the election period as one state at a time is excluded from the analysis. The results are similar for other outcome variables as well.

Figure 2.D.2: Robustness of Results on Murder to the Exclusion of States from the Analysis



Notes: This graph displays the coefficient of the variable 'Election Period' in a fixed effects regression of daily murder count on the election period, excluding states one at a time from the analysis.

2.D.3.2 ACLED results robust to excluding Jammu and Kashmir State

The (erstwhile) state of Jammu and Kashmir has the highest level of explosions/battles in the ACLED dataset. Since the state is not included in the IPC results, I show robustness of the ACLED results to the exclusion of the state from the analysis.

Table 2.D.8: Impact of Election Periods on Daily ACLED Count and Fatalities excluding Jammu & Kashmir

	Election Period	Constant	Observations
Battles	0.000142**	0.000273***	3976731
	(0.00006)	(0.00000)	
Explosions	0.0000944**	0.000116***	3976033
	(0.00004)	(0.00000)	
Protests	-0.00217***	0.00848***	4010381
	(0.00029)	(0.00001)	
Riots	0.00130***	0.00167***	3982974
	(0.00015)	(0.00001)	
St. Dev.	0.0000666**	0.0000909***	3975933
	(0.00003)	(0.00000)	
Viol. Civ.	0.000318***	0.000480***	3977706
	(0.00007)	(0.00000)	
Battles Fatalities	0.000106	0.000224***	3976731
	(0.00007)	(0.00000)	
Explosions Fatalities	0.0000860**	0.0000365***	3976033
	(0.00004)	(0.00000)	
Protests Fatalities	-0.00000626	0.00000359***	4010381
	(0.00000)	(0.00000)	
Riots Fatalities	0.0000837**	0.000114***	3982974
	(0.00003)	(0.00000)	
St. Dev. Fatalities	0.00000568	0.00000241***	3975933
	(0.00001)	(0.00000)	
Viol. Civ. Fatalities	0.0000822*	0.000257***	3977706
	(0.00005)	(0.00000)	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various outcomes of political violence as measured by the ACLED dataset at the daily-assembly constituency level using the full dataset. Rows 1-6 estimate the impact on the number of events. Rows 7-12 estimate the impact on the number of fatalities. St. Dev. = Strategic Developments. Viol. Civ. = Violence against Civilians. The erstwhile state of Jammu and Kashmir is excluded from the analysis. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. All regressions include constituency and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the assembly constituency level. No other covariates are included.

2.D.4 Results Hold for National Elections

I show that the results hold using national elections. Three national elections were held in the 2008-2019 period. Results using national elections can only use the partial sample, as national elections occur in phases, where, for some of larger states, voting within a state is broken up into phases. Each of the phases follows a slightly different schedule. As can be seen from Table 2.D.9, effects in the national elections are consistent with those seen in state-level elections, but are somewhat smaller in magnitude.[51]

[51] These smaller effects, if significantly different from state elections, could occur for a variety of reasons. National elections are understood to be less violent compared to state elections, and state governments, rather than the national government, are responsible for policing.

Table 2.D.9: Impact of National Election Periods on Daily Crime

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious Crime	(6) Election
National Election Period	0.0394***	0.0402***	-0.00563***	0.0552***	-0.00709***	0.00390***
	(0.005)	(0.005)	(0.002)	(0.005)	(0.001)	(0.001)
Constant	0.436***	0.627***	0.477***	0.237***	0.271***	0.000393***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30687498	30687498	30687498	30687498	30007658	30007658

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in a national election period on various crime outcomes at the daily-police station level using the partial dataset of all police stations. The dependent variable in Columns 1-6 refers to the number of police complaints filed, the number of criminal violations, the number of IPC violations, the number of non-IPC violations, the number of serious IPC violations (as defined by ADR (2014)), and the number of electoral violations under Chapter IXA of the IPC, respectively. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Columns 5 and 6 do not include data from the erstwhile state of Jammu and Kashmir as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

2.D.5 Results not Driven by Periodicity

Table 2.D.10 presents the main results of the paper using weekly, instead of daily, crime data. As can be seen, the results remain consistent with previous results.

Table 2.D.10: Impact of Election Periods on Average Weekly Crime

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious	(6) Election
Election	0.0446***	0.0233***	-0.0393***	0.0811***	-0.0279***	0.00846***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)
Constant	0.469***	0.805***	0.653***	0.279***	0.354***	0.000266***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PS FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8282583	8282583	8282583	8282583	8135814	8135814

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the weekly-police station level using the full dataset of all police stations. The dependent variable in Columns 1-6 refers to the number of police complaints filed, the number of criminal violations, the number of IPC violations, the number of non-IPC violations, the number of serious IPC violations (as defined by ADR (2014)), and the number of electoral violations under Chapter IXA of the IPC, respectively. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Columns 5 and 6 do not include data from the erstwhile state of Jammu and Kashmir as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

2.D.6 Robustness to Alternative Clustering

Table 2.D.11 presents the main results using the partial dataset where standard errors have been clustered at the assembly constituency-assembly period level.

Table 2.D.11: Impact of Election Periods on Daily Crime in Partial Dataset using Alternative Clustering

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious Crime	(6) Election
Election Period	0.0814***	0.0845***	-0.00623***	0.110***	-0.00792***	0.00968***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.001)	(0.000)
Constant	0.435***	0.626***	0.477***	0.236***	0.271***	0.000242***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30696004	30696004	30696004	30696004	30016164	30016164

Standard errors in parentheses

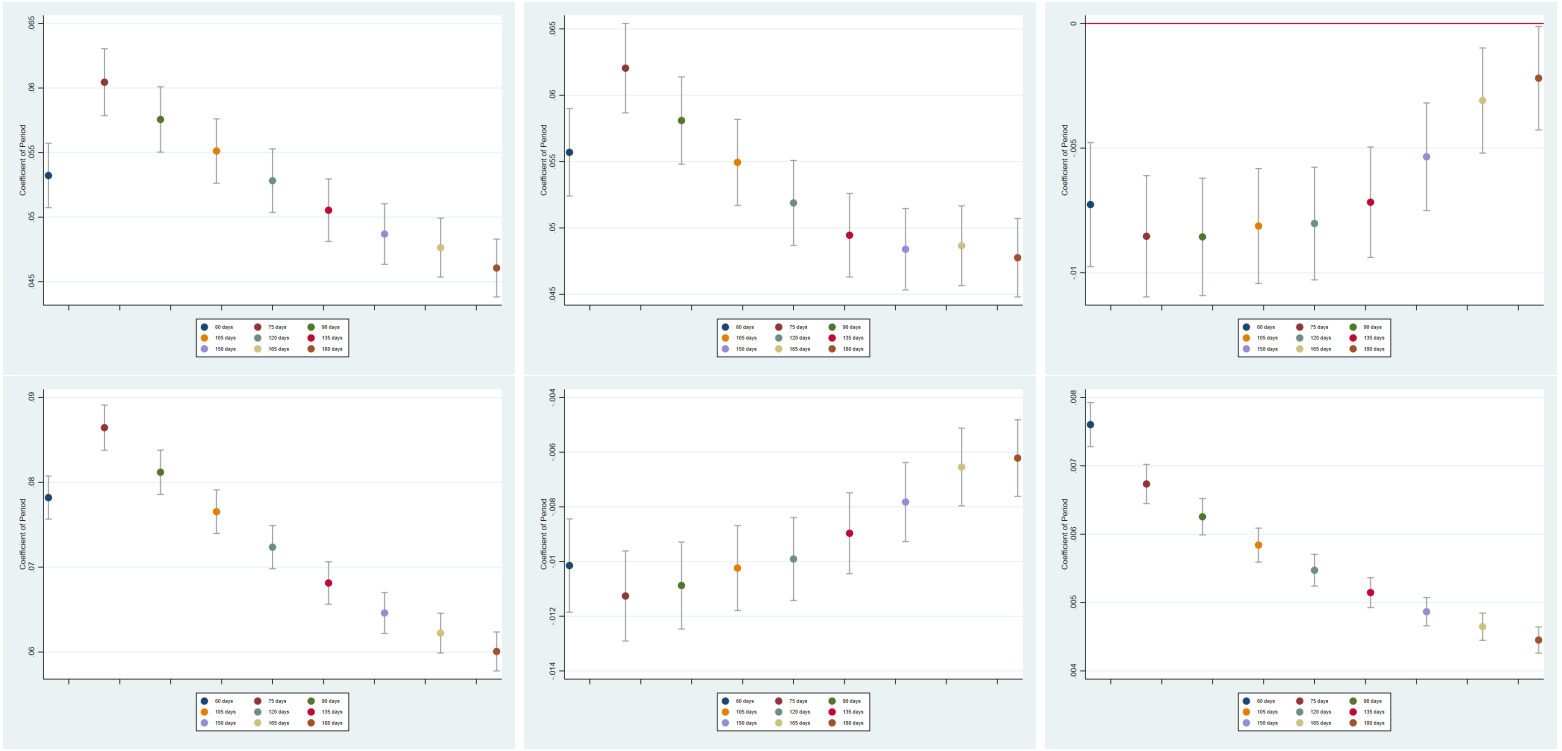
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the weekly-police station level using the partial dataset of all police stations. The dependent variable in Columns 1-6 refers to the number of police complaints filed, the number of criminal violations, the number of IPC violations, the number of non-IPC violations, the number of serious IPC violations (as defined by ADR (2014)), and the number of electoral violations under Chapter IXA of the IPC, respectively. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Columns 5 and 6 do not include data from the erstwhile state of Jammu and Kashmir as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the assembly constituency-assembly period level. No other covariates are included.

2.D.7 Robustness over Alternative Time Horizons

I broaden the definition of the election period beyond the official election period, considering up to 6 months in advance of an election taking place. Figure 2.D.3 shows the results for a more generally defined election period. As can be seen, the results remain significant, which confirms that they are not being driven by the official election period itself but hold even in other definitions of what the election period is. However, as we would expect, the results also begin to taper away in the direction of no effect as a longer pre-election period is considered. The changes in case counts, violation counts, non-penal code counts, and election crimes become smaller in magnitude the longer the definition of the election period, even as they remain significant. The decrease in crime counts also becomes smaller, moving in the direction of no change in IPC crimes closer to the 180-day mark. Serious crimes, on the other hand, increase, as I consider a longer pre-election period.

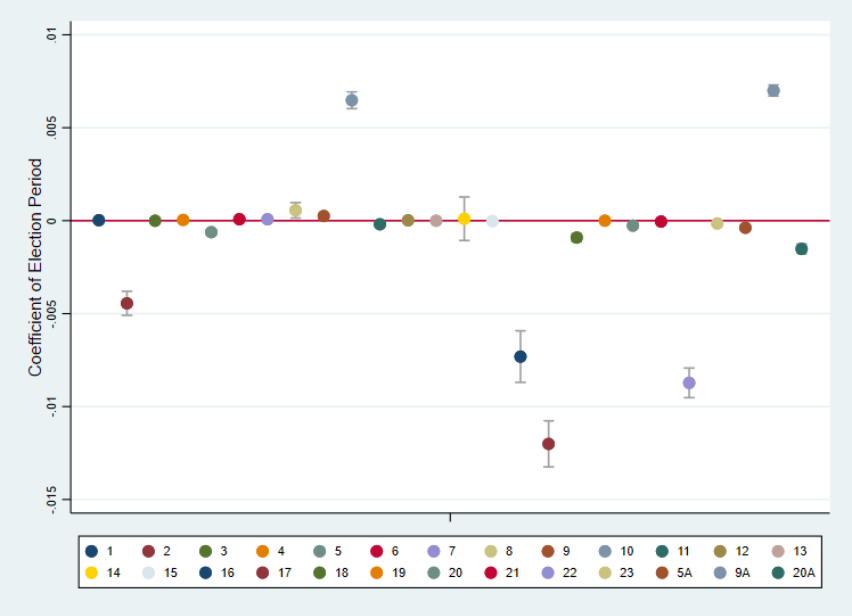
Figure 2.D.3: Effects Taper Off in Moving Away from the Election Period.



Notes: The graph presents the coefficients of the regression of the six main crime outcomes on the election period, defined as 60, 75, 90, 105, 120, 135, 150, 165, and 180 day periods before the date of the results of the poll. The 180-day period, for example, includes 180 days in the run-up to election. Since an average election duration is 66 days, the 180-day period includes an additional 114 days before the election schedule is announced.

2.E Sources of Changes in IPC Crimes

Figure 2.E.4: Coefficient of Election Period by IPC Chapter



Notes: This graph displays the coefficient of the variable 'Election Period' in a fixed effects regression of daily count of each IPC Chapter the election period with police station and unique week-year fixed effects. Data from the erstwhile state of Jammu and Kashmir is not included as the Indian Penal Code does not automatically apply to the state. The full sample is used for the analysis. Standard errors are clustered at the police station level.

As mentioned in Section 2.3, a majority of crimes are recorded against the IPC. From Table 2.8, it can be seen that there is a decline in the total number of offences registered under three key chapters of the IPC. Figure 2.E.4 presents the coefficient of the election period in a regression of the form of Equation 2.1 with the incidence of different chapters as the dependent variable. As we would expect under Hypothesis 2, significant reductions in crime can be seen in Chapter 16 (Offences affecting the Human Body, such as murder, hurt, restraint, assault, kidnapping, rape, etc.), Chapter 17 (Offences against Property, such as theft, extortion, cheating, trespass, etc.), Chapter 18 (Offences relating to Documents & Property Marks, such as forgery, counterfeiting, etc.), Chapter 20 (Offences Relating to Marriage), Chapter 22 (Criminal Intimidation, Insult & Annoyance), and Chapter 20A (Cruelty by Husband or Relatives of Husband). We also see declines in Chapter 2 (General Explanations), Chapter 5 (Abetment), and Chapter 5A (Criminal Conspiracy). Significant

increases in crime can be seen in Chapter 8 (Offences against Public Tranquillity, such unlawful assembly, rioting, promoting enmity between groups, etc.), Chapter 10 (Contempt of the Lawful Authority of Public Servants, obstruction, threats to public servants, non-appearance to summons, giving false information, etc.), and Chapter 9A (Offences relating to Elections, such bribery, undue influence, illegal payments in connection with election). There is no significant change in the incidence of crimes recorded under other chapters, for example, Chapter 14 (Offences Affecting Public Health, Safety, Convenience, Decency and Morals).

2.F Heterogeneity within Election Periods: Regression Tables

This section presents the results from the regression of various crime outcomes on the election sub-periods in the full and partial datasets. The base period for comparison is the non-election period. The various sub-periods are defined as follows. Sub-period 1: Date of announcement - Issue of notification. Sub-period 2: Issue of notification - Last date for nominations. Sub-period 3: Last date for nominations - Scrutiny of nominations. Sub-period 4: Scrutiny of nominations - Last date for candidate withdrawal. Sub-period 5: Last date for candidate withdrawal - Date of poll. Sub-period 6: Date of poll - Counting of Votes. Sub-period 7: Counting of Votes - Date of completion of election.

Table 2.F.12: Impact of Election Sub-Periods on Daily Crime in Full Dataset

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious Crime	(6) Election
Sub-Period=0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
Sub-Period=1	0.168***	0.199***	0.0224***	0.231***	-0.000332	0.00436***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.000)
Sub-Period=2	0.101***	0.122***	0.00980***	0.144***	0.000770	0.00854***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.000)
Sub-Period=3	0.0970***	0.111***	-0.00337	0.146***	-0.00268	0.0102***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.003)	(0.001)
Sub-Period=4	0.0791***	0.0932***	-0.00102	0.119***	-0.00322	0.0136***
	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.001)
Sub-Period=5	0.00498**	0.00986***	-0.0255***	0.0439***	-0.0240***	0.0300***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Sub-Period=6	-0.0587***	-0.0466***	-0.00379	-0.0670***	0.0117***	0.000541***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.000)
Sub-Period=7	-0.0376***	-0.0535***	-0.0111***	-0.0591***	0.000610	0.000140
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.000)
Constant	0.522***	0.729***	0.542***	0.297***	0.307***	0.000166***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29149945	29149945	29149945	29149945	29149945	29149945

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.F.13: Impact of Election Sub-Periods on Daily Crime in Partial Dataset

Count	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code	(5) Serious Crime	(6) Election
Sub-Period=0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
Sub-Period=1	0.196***	0.207***	0.0174***	0.238***	-0.0000138	0.00431***
	(0.004)	(0.005)	(0.003)	(0.005)	(0.002)	(0.000)
Sub-Period=2	0.118***	0.121***	-0.00362	0.154***	-0.00726***	0.00828***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.002)	(0.000)
Sub-Period=3	0.114***	0.115***	-0.0112*	0.158***	-0.00950**	0.00872***
	(0.006)	(0.008)	(0.006)	(0.007)	(0.004)	(0.001)
Sub-Period=4	0.108***	0.110***	-0.00162	0.143***	-0.00515	0.0128***
	(0.005)	(0.007)	(0.005)	(0.006)	(0.003)	(0.001)
Sub-Period=5	0.0207***	0.0191***	-0.0294***	0.0589***	-0.0261***	0.0286***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)
Sub-Period=6	-0.0431***	-0.0469***	-0.0193***	-0.0456***	-0.00320*	0.000658***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.000)
Sub-Period=7	-0.0169***	-0.0234***	0.00271	-0.0352***	0.00429*	0.000123
	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)	(0.000)
Constant	0.435***	0.626***	0.477***	0.236***	0.271***	0.000241***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30696004	30696004	30696004	30696004	30016164	30016164

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.G Lists of Acts Included in Analysis

In most of the cases, the acts used in the analysis have been included alongside the analysis. However, in a few cases, multiple acts were combined to produce the total number of cases that were used in the analysis and could not be included in the main text. This was particularly the case when a set of acts is enacted at the state level, for example, excise acts or destruction of public property. In those cases, all the relevant state-level excise acts are combined for the purpose of analysis. Where several state acts have been combined and are not included in the main text, they are given below.

2.G.1 Police Acts

POLICE ACT, 1861 POLICE ACT, 1949 MAHARASHTRA POLICE ACT, 1951 THE POLICE (PONDICHERRY AMNDT) ACT, 1966 THE TAMIL NADU CITY POLICE ACT 1888 NAGALAND ARMED POLICE ACT, 1996 KARNATAKA POLICE ACT, 1963 BOMBAY POLICE ACT, 1951 KERALA POLICE ACT, 1960 DELHI POLICE ACT, 1978 UTTARAKHAND POLICE ACT, 2007 MAHARASHTRA STATE RESERVE POLICE FORCE ACT, 1951 THE MAHARASHTRA VILLAGE POLICE ACT, 1967 POLICE (ORISSA AMENDMENT) ACT, 1976 KARNATAKA POLICE ACT KARNATAKA POLICE ACT, 2011 SIKKIM POLICE ACT, 2008 PUNJAB POLICE ACT, 2007 ASSAM POLICE ACT, 2007 RAJASTHAN POLICE ACT, 2007 HIMACHAL PRADESH POLICE ACT, 2007

2.G.2 Noise Control

THE PUNJAB INSTRUMENTS (PREVENTION OF NOISES)ACT THE PUNJAB INSTRUMENTS (CONTROL AND NOISES) ACT, 1956. RAJASTHAN NOISE CONTROL ACT 1963 HIMACHAL PRADESH INSTRUMENTS (CON-

TROL OF NOISES) ACT, 1969 M.P. CONTROL OF MUSIC AND NOISES ACT, SAMVAT-2008 NOISE POLLUTION (REGULATION AND CONTROL) RULES, 2000 M.P. NOISE POLLUTIONS ACT 1985 INSTRUMENT (CONTROL OF NOISES) ACT,1959 CHHATTISGARH NOISE POLLUTION CONTROL ACT, 1985 THE NOISE POLLUTION (REGULATION AND CONTROL)RULES 2000

2.G.3 State Prevention of Defacement of Property Acts

PREVENTION OF DAMAGE TO PUBLIC PROPERTY ACT, 1984 THE TAMIL NADU PROPERTY(PREVENTION AND DAMAGE AND LOSS) ACT 1992 WEST BENGAL DEFACEMENT OF PROPERTY ACT PREVENTION OF DAMAGE TO PUBLIC PROPERTY ACT, 1984 PREVENTION OF DESTRUCTION AND LOSS OF PROPERTY ACT, 1981 THE GOA PREVENTION OF DEFACEMENT OF PROPERTY ACT 1988 MAHARASHTRA PREVENTION OF DEFACEMENT OF PROPERTY ACT, 1995 THE TRIPURA PREVENTION OF DEFACEMENT OF PROPERTY ACT, 1976 THE GOA PREVENTION OF DAMAGE TO PUBLIC PROPERTY ACT PREVENTION OF DEFACEMENT OF PROPERTY ACT 1985 PUBLIC PROPERTY(PREVENTION OF DAMAGE) ACT1985 WEST BENGAL PREVENTION OF DEFACEMENT OF PROPERTY ACT 1976 PUNJAB PREVENTION OF DEFACEMENT PROPERTY ORDINANCE ACT 1997 DELHI PREVENTION OF DEFACEMENT OF PUBLIC PROPERTY ACT, 2007 JHARKHAND PREVENTION OF DEFACEMENT OF PROPERTY ACT, 1985 U.K PREVENTION PUBLIC PROPERTY ACT SIKKIM-PREVENTION OF DAMAGE TO PUBLIC PROPERTY ACT, 1984 RAJASTHAN PREVENTION OF DEFACEMENT OF PROPERTY ACT, 2006 MAHARASHTRA PREVENTION OF DEFACEMENT OF PROPERTY ACT, 1995 THE HARYANA PREVENTION OF DEFACEMENT OF PROPERTY ACT, 1989 CHHATTISGARH PROHIBITION OF VIOLENCE AND LOSS/DAMAGE OF HEALTH WORKERS AND HEALTH CENTERS PROPERTY 2010 PUNJAB PREVENTION OF DAMAGE TO PUB-

LIC AND PRIVATE PROPERTY ACT, 2014

2.G.4 Excise Acts

A.P EXCISE ACT 1968 ASSAM EXCISE ACT, 1910 BIHAR EXCISE ACT GOA EXCISE DUTY ACT AND RULES, 1964 THE PUNJAB EXCISE ACT, 1914, 1 OF 1914 THE PUNJAB EXCISE ACT, 1914 RAJASTHAN EXCISE ACT 1950 THE U.P. EXCISE ACT NAGALAND EXCISE ACT KARNATAKA EXCISE ACT, 1965 PUNJAB EXCISE (H.P AMENDMENT) ACT, 1965 A.R EXCISE ACT, 1993 ORISSA AND BIHAR EXCISE ACT 2 OF 1915 ANDAMAN EXCISE RULES, 1934 REGULATION III OF 1876 PUNJAB EXCISE ACT, 1914 M.P. EXCISE ACT, 1915 EXCISE ACT 1958 (1901 AD) THE TRIPURA EXCISE ACT, 1987 PONDICHERRY EXCISE ACT,1989 DELHI EXCISE ACT, 2009 THE ORISSA EXCISE ACT 2008 JHARKHAND EXCISE ACT, 1915 HIMACHAL PRADESH Excise Act, 2011 CHHATTISGARH EXCISE ACT, 2015 DADAR & NAGAR HAVELI EXCISE DUTY REGULATION, 1969 ASSAM EXCISE AMENDMENT ACT, 2018 KERALA ABKARI ACT ABKARI ACT

2.G.5 Gambling

MAHARASHTRA PREVENTION OF GAMBLING ACT, 1887 THE PUBLIC GAMBLING ACT, 1867 PUBLIC GAMBLING (MADHYA PRADESH) ACT, 1976 THE PUBLIC GAMBLING ACT, 1867, 3 OF 1867 THE PUNJAB GAMBLING ACT, 1867 THE PUNJAB GAMBLING ACT 1867 THE TAMIL NADU GAMING ACT 1930 A.P GAMING ACT 1974 RAJASTHAN PUBLIC GAMBLING ORDINANCE 1949 LOTTERY REGULATION ACT 1998 M.P. BETTING ACT ORISSA PREVENTION OF GAMBLING ACT 1954 PUBLIC GAMBLING ACT, 1867 PUBLIC GAMBLING ACT, 1955 THE GOA, DAMAN AND DIU PUBLIC GAMBLING ACT 1976 U.P PUBLIC GAMBLING ACT 1867

2.G.6 Prohibition

MAHARASHTRA PROHIBITION ACT, 1949 NARCOTIC DRUGS AND PSYCHOTROPIC SUBSTANCES ACT, 1985 TAMIL NADU PROHIBITION ACT 1937 THE BOMBAY PROHIBITION ACT, 1949 NARCOTIC DRUGS AND PSYCHOTROPIC SUBSTANCES ACT, 1985 THE BOMBAY PROHIBITION ACT, 1998 ASSAM LIQUOR PROHIBITION ACT, 1952

2.H Changes in Crimes against Women and SC/STs before an Election

This section studies how crimes against individuals of certain groups – women, SC/STs – change in advance of the official election period, examining whether intimidation of individuals in these groups takes place in the run-up to elections. I define '60 days prior', a dummy variable that takes the value 1 in the 60-day period prior to an election announcement, and the value 0 otherwise. As can be seen from the Table 2.H.14, there is no significant relationship between the number of incidents recorded under IPC chapters XX (marriage-related offences) and XXA (cruelty of husband and family) in the 2-month period prior to election announcement. On the other hand, there is an increase in the incidence of crimes recorded against SC/STs prior to an election. As expected, and consistent with the main results of the paper, there is a decline in offences against women and SC/STs during the election period, which may be driven by changes in occurrence as well as enforcement. These results may point towards the differences in the political nature of crimes against women (which are not likely to be political, and may be driven by changes in enforcement), and of crimes against SC/STs (which may be driven by political activity in this context).

Table 2.H.14: Impact of 60-day Prior to Election Period on Daily Crimes Against Women, SC/STs

	(1) Marriage	(2) Cruelty	(3) SC/ST Act
60 days prior	0.0000452	-0.000116	0.000462***
	(0.000)	(0.000)	(0.000)
Election Period	-0.000266***	-0.00150***	-0.000412***
	(0.000)	(0.000)	(0.000)
Constant	0.00169***	0.0145***	0.00600***
	(0.000)	(0.000)	(0.000)
Police Station FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Observations	54005259	54005259	46604990

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an six-month period prior to the announcement of the election on crimes against women (IPC Chapters on Offences against Marriage and Cruelty by Husband, XX and XXA, respectively), and against SC/STs under the SC/ST (Prohibition of Atrocities) Act at the daily-police station level using the full dataset of all police stations. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Data from the erstwhile state of Jammu and Kashmir is not included. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the police station level. No other covariates are included.

2.I Electoral Cycles in Constituencies with Criminal Politicians

Finally, I look at whether and how election cycles are different in places where criminal politicians are elected (linking Chapters 2 and 3). To do so, I use the partial dataset, where each police station has a constituency mapping. I include the variable *Criminal*, which is 1 if a criminal was in office during the non-election period and 0 if a non-criminal was in office in the non-election period. During an election period, *Criminal* takes the value of the individual who was in office in the *preceding* non-election period. I include all races, including those where criminals won against other criminals and non-criminals won against other non-criminals. Results are shown in Table 2.I.15. For comparison, the main results in the partial dataset are shown in Table 2.D.4.

Table 2.I.15: Impact of Election Periods on Daily Crime in Constituencies with Criminal Politicians

	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal	(5) Serious Crime	(6) Election
Election Period	0.0925***	0.0982***	-0.00686*	0.130***	-0.00770***	0.0123***
	(0.005)	(0.006)	(0.004)	(0.005)	(0.003)	(0.001)
Criminal	-0.00763	-0.00304	-0.00455	-0.000383	-0.00422	0.0000561
	(0.009)	(0.012)	(0.009)	(0.009)	(0.005)	(0.000)
Criminal*Election	0.00582	0.0157	0.00821	0.0124	0.00162	0.00307***
	(0.008)	(0.011)	(0.007)	(0.009)	(0.004)	(0.001)
Constant	0.466***	0.660***	0.502***	0.254***	0.286***	0.000239***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.000)
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23870129	23870129	23870129	23870129	23399739	23399739

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression estimates of the impact of being in an election period on various crime outcomes at the daily-police station level using the partial dataset of police stations, that is, police stations that can be mapped uniquely to assembly constituencies. The dependent variable in Columns 1-6 refers to the number of police complaints filed, the number of criminal violations, the number of IPC violations, the number of non-IPC violations, the number of serious IPC violations (as defined by ADR (2014)), and the number of electoral violations under Chapter IXA of the IPC, respectively. The dependent variable in all regressions is transformed using the inverse hyperbolic sine transformation. Columns 5 and 6 do not include data from the erstwhile state of Jammu and Kashmir as the Indian Penal Code does not automatically apply to the state. All regressions include police station and unique week-year fixed effects, and are estimated using the 'reghdfe' command. Standard errors (in parentheses) are clustered at the assembly constituency level.

CHAPTER 3

Law Makers or Law Breakers? The Impact of Criminal Politicians on Local Crime

Abstract

With their control over local criminals and the local police, criminal politicians have the ability to potentially impact local crime. Using some of the most detailed and granular data on crime in India, this article estimates the impact of politicians with criminal backgrounds on crime, testing whether criminal politicians are less or more effective than their non-criminal counterparts in providing security for members of their constituency. On one hand, this speaks to a theory where criminal politicians are elected not despite of, but because of, their ability to control crime and get things done in an environment with weak rule of law. On the other hand, given their criminal backgrounds and political control over local police, criminal politicians may seek to consolidate their rent-seeking interests during their time in office. Using a close election regression discontinuity design, I find that having a criminal politician in office lowers weekly counts of serious crimes by 23.6%, even though the total number of complaints filed remains unchanged. This reduction in crime seems to be partly driven by reduced recording of crime. I find that non-serious and serious criminals affect different kinds of crimes, suggesting a differential role played by signalling and rent-seeking motives.

3.1 Introduction

One in every three elected representatives in the lower house of the Indian Parliament and in state Legislative Assemblies is criminally accused. With their criminal backgrounds and networks, control over local police, and importance in political parties, who rely on them for money and muscle power, criminal politicians have the ability to potentially impact local crime in a significant way. The incentives to use their position to consolidate gains from crime (reputational, monetary, etc.) run up against their incentives to be re-elected, in a context where elections are competitive, electoral races are close, and a few thousand votes can make a difference.[52]

However, we know little about what happens to crime when a criminally accused politician is elected. This paper aims to evaluate the causal impact of having such a politician in elected office at the state level on local crime, and to understand the various mechanisms through which this influence may be exerted. I answer this question in a detailed and systematic way by bringing what is possibly the most granular dataset on crime and politics to the table. Previous research on crime in India has used annual, district-level data, masking several heterogeneities and trends in crime within a district and year. I obtain a case-level administrative dataset of all crime in 33 states and Union Territories over the last decade in India and collapse it to over 3.6 million observations at the police station-week level. I further work with the Police Departments in 27 states and Union Territories to map police jurisdictions and political boundaries for the first time. I combine this with information on electoral races over the 2008-2019 period and prepare a dataset covering 26 states and Union Territories, or over 83% of India's population. Using a regression discontinuity design, I aim to identify causal impact.

I estimate that there is a 23.6% decrease in weekly serious crime counts in police

[52]The median margin of victory in my sample is about 11,000 votes, or less than 3 percent of an average constituency's population.

stations that come under the jurisdiction of criminal constituencies, even though the total number of complaints filed remains unchanged. The sharp decline in serious crime is robust to a number of checks on the regression discontinuity specification, as well as checks on data coverage and timing. I then try to answer two important questions about the source of the decline in crime - is it real, and where does it come from? Using a specific subset of crimes that are hard to under-report (for example, murders) or collected from third-party sources (for example, political violence data from the Armed Conflict Location and Events Data (ACLED) Project), I try to disentangle whether the changes in crime are driven by actual changes or lower levels of crime recording in criminal constituencies. The results show that there is no significant difference in this subset of crimes between areas where a criminal politician narrowly won or lost, pointing towards the role of under-recording in criminal areas. However, these results are suggestive at best, as the kinds of crimes for which third-party data is available are not the crimes that change in the overall sample in the first place, and our ability to extrapolate from the results on murder is limited.

To better understand what may be driving these results, I explore heterogeneities in the impact of criminal politicians on crime and recording. In this context, several politicians run up against the law as a part of political activity and campaigning, such as protests. For example, one in four politicians is accused of being a member of an 'unlawful assembly'. Such 'non-serious' criminal behaviour might be quite different from 'an attempt to murder', for example. This distinction could be particularly relevant in the context where both 'serious' and 'non-serious' criminals would like to reduce the recording of crime, albeit for different reasons. While 'non-serious' criminals might be interested in 'signalling' their effectiveness to constituents (for example, by being willing to go to jail to protect the interests of their community), 'serious' criminals might, in addition, be interested in safeguarding their rent-seeking interests and reducing the recording of crimes against their associated criminal counterparts. To explore these channels, I look at the impact of

'serious' criminals and 'non-serious' criminals separately, and find that the decline in crime where 'non-serious' criminals are elected is 41.8%, compared to a decline of 16.4% in places where serious criminals are elected. Yet, the change in murders for both these groups distinctly is still no different from zero. Finally, to study the impact of rent-seeking interests, I incorporate the role of the precise criminal profile of the criminal, and find that it matters. For example, being accused of crimes against property or religion affects the incidence of those very kinds of crimes differently compared to other criminal politicians who are not accused of that crime.

This is one of the first papers to directly study the impact of criminal politicians on crime outcomes. Chemin (2012) explores the role of criminality as a mechanism to explain reduced incomes of individuals living in criminally-dominated districts. Other research has highlighted the impact of criminal politicians on other aspects of economic development. For example, researchers have found empirical evidence of significant negative impacts of having a criminal politician in office on growth, as measured by night-time lights (Prakash et al., 2019), on private investment (Nanda and Pareek, 2019), and on consumption (Chemin, 2012).[53] Gehring et al. (2019) find lower utilization rates of the local area development fund by criminally accused Parliamentarians. However, most analyses of criminal politicians are limited either by the unavailability of narrow geographic information or by a narrow time horizon. For example, Prakash et al. (2019) find that electing a criminal politician results in a 24-percentage point lower yearly growth, measured by the intensity of night-time lights. Their sample is restricted to all state elections in India held between 2004 and 2008, prior to the delimitation of the constituency boundaries in 2008, and hence they observe only one election per state. Similarly, Chemin (2012) uses district-level data to compare individual outcomes of people living in districts where there were fewer or more criminal politicians. In contrast, I have as many as three elections for some constituencies, and police station-level outcomes data covering 26 states and

[53]Nanda and Pareek (2019), however, find that the reduction in private consumption is offset by a roughly equivalent increase in public investment by state-owned firms.

Union Territories.

Second, I examine the role of differential impact of various aspects of criminal behaviour – looking at 'serious' versus 'non-serious' crime, a politician's specific criminal background, etc. These are relevant because even as some of the literature has documented the negative economic and development impacts of criminal politicians, others have tried to understand the nature of rule of law and governance that results in the election of such criminals. In an ethnographic study of local political networks in Ahmedabad, Gujarat, India, Berenschot (2011) argues that the regular cooperation between criminals and politicians is not a 'sign of moral decay', but a result of the nature of political competition and inaccessibility of the state to its poorer citizens. Vaishnav (2017) suggests that criminal politicians are elected not despite, but because of, their criminal background. He hypothesizes that criminal politicians have higher 'credibility,' which he uses a short- hand for four alternative mechanisms – redistribution, coercion, social insurance, and dispute resolution. In each of these four cases, criminal politicians use criminality as a signal of their ability to protect the interests of their community.[54] In this setting, trying to disentangle the differential impacts of different kinds of crime can help us understand more about the rent-seeking and signalling behaviour by political candidates.

Finally, this paper also contributes to the literature studying the impact of politics on the recording of crime. Iyer et al. (2012) show that political representation matters for crime recording, as recording of crimes against women by the police increases when the elected local councillor is a woman. Recent work by Ahmed et al. (2021) in the context of Pakistan finds that police are less likely to record and process citizen complaints in areas that support the governing political party, and that political alignment matters for the registration of police complaints. The results in this paper suggest that the decline in crime in criminal areas is at least partly driven by lower levels of recording by the police in criminal constituencies.

[54]This may be a true signal (when crime actually falls), or a false signal (when recorded crime falls but there is no actual change in crime).

This paper is structured as follows. Section 3.2 lays out the institutional context of criminal politicians and crime in India, and presents the four main sources of data used in the paper. Section 3.3 discusses the empirical methodology, and checks for the validity of the identifying assumptions of the regression discontinuity design. Section 3.4 presents the main results. Section 3.5 discusses the role of actual vis-à-vis recorded changes in crime. Section 3.6 examines the role of criminal types and crime profiles that drive some of the results, and Section 3.7 concludes.

3.2 Institutional Context and Data

In this section, I discuss the constitutional, electoral, and criminal justice context within which criminal politicians compete in elections and once in office, control the law and order machinery of the state. I focus this analysis on state governments, which form the second tier in India's quasi-federal system. State Legislative Assemblies have the power to make laws on subjects in the State List of the Indian Constitution, including public order, police, prisons, public health, agriculture, irrigation, and local governments. They also allocate funds in the form of the state budget. As a result, I look at the role of state-level, rather than national-level, representatives.[55]

3.2.1 Context: Criminal Politicians and Crime

As of 2019, one in three sitting Members of Legislative Assembly (MLAs) across all states had at least one declared criminal case registered against them. Of the MLAs with at least one criminal case registered against them, 65 percent have been charged with committing serious crimes, such as murder or rape. The definition of serious

[55] I compare the impact of criminal parliamentarians at the national level vis-à-vis criminal state legislators as a possible mechanism in Appendix 3.I.

crimes follows ADR (2014) and is described below.[56] Throughout this paper, I use the term criminal politicians to refer to politicians who are criminally accused rather than convicted. A criminal accusation, as defined here, is not an unverified criminal charge levied against a politician, but rather a case for which initial investigation has been conducted and cognizance has been taken by the courts. Securing convictions in court, on the other hand, is a long-drawn out outcome given the state of the Indian criminal justice system (Vaishnav, 2017). Under the current system, politicians who are accused, but not yet convicted of crime, can continue to contest elections and hold office.

Vaishnav (2017) describes the historical emergence of politicians with criminal backgrounds, which took place through a process of 'vertical integration' as increasing political uncertainty around the 1970s and 1980s weakened contracts between criminals and politicians. Previously, criminals were hired by politicians during election time, and received money and political protection from prosecution in turn. However, with the weakening of one-party dominance in Indian politics, these relationships between criminals and politicians became fraught with agency issues, and criminals began to directly contest elections using the social capital that came as a result of their access to resources, ability to deliver, and their links with and reputations in local and ethnic communities.

This preponderance of criminally-accused politicians that emerged in the context of a nexus between criminals, politicians, and police in various parts of the country was identified as early as 1993 by the Government of India. The Vohra Committee investigated the activities of crime syndicates that were purportedly linked with and were being protected by government functionaries and political leaders. The resulting report, apparently too explosive to be published in its full form, suggested that the formation of such a powerful criminal network was not possible without the patronage of politicians and protection of relevant government departments,

[56] I explore the distinction in the impact of such 'serious' versus 'non-serious' criminals in Section 3.6.

including Customs, Income Tax, and the Police. In particular, the report alluded to the cross-cutting networks of individuals who moved freely between crime and politics, and whose significant money and muscle power mattered to political parties at the time of elections (Ministry of Home Affairs, Government of India, 1993).

Despite this acknowledgment of the links between crime and politics, the nature of organization of crime in South Asia is under-researched and not well understood (Michelutti et al., 2018). In India, there is a "long history of the lines between organized criminal activity and politics being blurred" (Global Initiative Against Transnational Organized Crime, 2021a). Criminal actors in the region are most likely to be state-embedded actors, or loosely-organized criminal networks, rather than mafia-style groups (Global Initiative Against Transnational Organized Crime, 2021b). However, our understanding of the relationships between crime and politics, and the ways in which the informal economy brushes with organized crime and politics is not well-developed.[57] Further, criminal politicians can also be found in several other developed and developing country contexts as well, including in Brazil, Nigeria, the Philippines, Pakistan, Jamaica, and the US. The degree of their linkages with organized and unorganized crime as well as their control over the local police varies in each of these contexts.

This paper aims to study the relationship between criminal politicians and local crime using data from India and test whether the election of criminal politicians leads to an increase or decrease in local crime. The political control of criminals and the police could encourage perverse incentives and undesirable outcomes in the sphere of law, order, and justice. Aidt et al. (2013) suggest that Indian political parties are more likely to select criminal candidates in the face of greater electoral competition, as such candidates have the capacity to intimidate opposition voters with the use

[57]Barnes (2017), in his work on the alternative relationships between organized crime and politics, distinguishes between four alternate sets of crime-state arrangements - confrontation (high competition), enforcement-evasion (low competition), alliance (low collaboration), and integration (high collaboration). This may provide one lens for contextualizing and analysing these relationships in different Indian states.

of violent pre-electoral tactics and prevent them from going to the polls. Wilkinson (2004) argues that politicians in contemporary India both cause communal riots, and have the power to prevent them, through their control of the police.[58] Murray (2020), in his study of the National Rural Employment Guarantee Scheme in India, finds that criminals' core advantages in providing for constituents derives from their capacity for violence. Asher and Novosad (2020) find that as local rents increase, criminally accused politicians are more likely to engage in more criminal behaviour and to see their personal wealth increase. In sum, politicians could use their control over local criminal activity and police to signal the delivery of peace and security, while building a 'strongman' reputation in their community, but they could just as easily use their criminal background to increase lawlessness and their personal rents, resulting in worse security outcomes for areas under their control. In fact, in line with the concept proposed by Olson (1993), criminal politicians may reduce crime in the community by setting themselves up as 'stationary bandits', while at the same time consolidating their rents from crime. In this paper, I think of different kinds of criminal politicians as having different motivations - for example, 'serious' criminals may have rent-seeking motives for crime reduction, in addition to signalling their ability to protect their community.

Crime and policing are state-level subjects in India, which means that the state government is responsible for maintaining law and order and undertaking policing. The Indian Penal Code, or the IPC, is the official criminal code of India, covering all substantive aspects of criminal law. The IPC is divided into 23 chapters and over 500 sections that cover a wide range of offences, and provide explanations and exceptions. In addition to the IPC, governments at both the national and state levels have enacted laws which regulate various aspects of society, security, and the economy, and include criminal provisions. Examples of these laws include the Dowry Prohibition Act, 1961, the Prevention of Corruption Act, 1988, and the Scheduled

[58] Riots are a product of the political incentives at the state and local levels, including the intensity of local political competition and the electoral interests of state governments in protecting minorities (Wilkinson, 2004).

Caste and Tribe (Prevention of Atrocities) Act, 1989. As discussed before, the framework for administration of crime in India is given by the Code of Criminal Procedure (CrPC). A First Information Report (FIR) is registered by the police when they receive information about a criminal offence or offences. Once a FIR has been filed, the police begin their investigation.

As mentioned previously, I focus on state-level elections, which are held every five years, and different states are on different election year cycles. Candidates run in a highly competitive races in a first-past-the post system to represent single-member constituencies as a Member of Legislative Assembly (MLA) in the State Assembly or *Vidhan Sabha*. There are a total of 4,120 assembly constituencies spread across 31 states and union territories in the country.[59] Delimitation of constituency boundaries was last undertaken in 2008. As per the latest delimitation, each assembly constituency seat represents an average population of 400,000 people (Gulzar and Pasquale, 2017).

3.2.2 Data

The data for this paper comes from four main sources - administrative crime data, mappings of police stations to political constituencies, affidavit data of state-level politicians and, finally, electoral data of state elections held over the 2008-2019 period.

3.2.2.1 Administrative Crime Data

I obtain an administrative dataset of case-level crime data for over a decade from the National Crime Records Bureau (NCRB). This dataset contains information on every FIR recorded in 14,970 police stations across 33 states and Union Territories

[59]Union territories are administrative units governed directly by the central government. Union Territories do not have their own elected legislatures, except for Puducherry, and the National Capital Territory of Delhi.

(UTs) over the 2008-2019 period. This case-level data has been recorded in the electronic Crime and Criminal Tracking Network System (CCTNS) adopted by Police Departments across the country.

Previous research on crime in India has mostly used the 'Crime in India' statistics, which are published annually by the NCRB since 1953. These statistics are compiled at the state and district levels, from case-level data like the one I am using. The administrative data used in this paper has several advantages over the aggregated NCRB data. First, the data is available at the police station level, which is a narrower geographic unit and allows me to match crime records to the constituency level, which is not possible with district-level data. Second, since each case recorded has information on the date and time of the crime, it allows me to disaggregate the crime trends within the year, especially during the run-up to, and immediately after, the election. Third, this data also allows me to examine the exact sections and acts that are being violated, rather than looking at the broad categorizations that are published in the NCRB data.[60] Finally, the published NCRB data uses the Principal Offence Rule for counting crime, which means that when there are multiple violations in one FIR, only the most serious is counted (National Crime Records Bureau, 2019).[61]

To undertake the analysis, I collapse the case data into a panel at the police station-week level with over 3.6 million observations, using information on the FIR registration number, as well as on acts and sections against which cases were registered. I consider five main outcome variables - the number of cases registered (case count), the number of violations (violation count), the number of IPC and non-IPC violations (crime count and non-penal code count, respectively), and the number of serious IPC violations (serious crime count). To measure serious crime count, I follow the criteria laid out by the Association of Democratic Reforms (2014). As

[60]The NCRB publishes information under aggregate heads such as IPC crimes, crimes against women, crimes against children, cyber crimes, etc.

[61]For example, if a complaint contains charges of both rape and murder, only the murder case is included in the aggregate statistics.

per this definition, charges are considered to be serious if the maximum punishment for the offence committed is of five years or more; the offence is non-bailable; the offence pertains to an electoral violation; the offence is related to the loss to exchequer; the nature of the offence is related to assault, murder, kidnap, rape; or the offence relates to crimes against women.

Table 3.1: Summary Statistics of Crime at the Week-Police Station Level

Variable	Obs	Mean	Std. Dev.	Min	Max
Weekly Case Count	3655194	5.021	8.029	0	656
Weekly Violation Count	3655194	11.323	17.875	0	2108
Weekly Crime Count	3655194	8.222	14.17	0	2099
Weekly Non-Penal Code Count	3655194	3.101	7.296	0	651
Weekly Serious Crime Count	3567514	3.301	6.172	0	892

Notes: The table presents summary statistics of five different measures of crime where each observation is a week-police station unit. This is a sample of the 26 states and union territories over the 2008-2019 period. I only include crime recorded in non-split police stations, and do not include the election periods. The state of Jammu and Kashmir records the IPC differently from the rest of the country and is excluded from the statistics on serious IPC counts.

3.2.2.2 Mappings of Administrative and Political Units

Second, I map each police station to the assembly constituency it is assigned to. Political and administrative boundaries overlap haphazardly in India, which creates challenges for mapping any kind of socioeconomic data to political boundaries. In many cases, mappings may exist but are not known outside of the local bureaucracy. I worked with the state police departments of 27 states to obtain a mapping of each of the police stations in their jurisdiction to an assembly constituency. Such a mapping is being used for the first time in empirical research to map crime outcomes to political constituencies.

In some cases, since the political and administrative boundaries overlap haphazardly, the jurisdiction of a single police station can be spread across multiple assembly constituencies, each with a different politician in power. Since such split police stations could register cases from individuals in multiple constituencies, crime recorded in split police stations cannot be attributed to any particular constituency. For the purpose of my analysis, I only look at police stations that are not split in this

way. Further information on police station types and their mapping can be found in Appendix 3.C.

Because I exclude all split police stations from the analysis, I do not aggregate the police station data to the constituency level, as this could lead to a biased outcome measure in constituencies where more or less police stations are included. Hence, my entire empirical analysis using the administrative data is conducted at the police station level.

3.2.2.3 Politicians' Criminal Records

Third, I scrape data from affidavits of 106,994 political candidates who run in state-level elections beginning 2004 and obtain biographical, educational, financial and criminal details of candidates (Association of Democratic Reforms, 2021). Under a 2003 Supreme Court ruling, each candidate is required to make mandatory public disclosures about their criminal, financial and educational background, including assets and liabilities, as well as any criminal cases that they have been convicted of or are pending against them. These affidavits have become a valuable source of understanding political behaviour and answering important political economy questions (for example, Fisman et al. (2014)). Examples of political affidavits filed by candidates are given in Appendix 3.A.

30.6% of all candidates in the sample have at least one criminal charge against them, with a maximum of 64 cases registered against an individual. Table 3.2 presents the summary statistics of the average number of cases and charges against all criminals (including both winners and runners-up) in the sample. Those with at least one criminal case against them face an average of 9.7 violations of IPC sections and 2.4 violations of serious IPC sections.

Given the environment of weak enforcement, there are three main concerns with the measurement of politicians' crime. First, it is possible that those who appear to be

Table 3.2: Summary Statistics of Crime Counts by Criminal Politicians

Variable	Obs	Mean	Std. Dev.	Min	Max
Criminal Cases	3459	3.02	4.284	1	64
IPC Count	3452	9.744	16.966	0	321
Serious IPC Count	3452	2.41	4.405	0	65

Notes: The table presents summary statistics of three different measures of criminal activity of politicians for elections over the 2008-2019 period. Each observation represents a unique constituency-assembly period. The sample of this table includes winners and runners-up from electoral races for which there is a police station-constituency match. A politician must be accused of at least one crime to be included.

non-criminals in the data are actually criminals and are much better at avoiding crime charges. While this is possible, there is extensive scrutiny of the affidavits filed by non-governmental organizations, the media, as well as political opponents. Second, those who are criminals in the data might actually be non-criminals facing made-up or fake criminal charges. However, the cases I consider are those that are self-reported by politicians, for which cognizance has been taken by the courts. Third, politics might itself affect the difference between prosecution and conviction. Recent research shows that MLAs from the party in government are more likely to get their cases disposed of, without conviction, during the government's tenure, while MLAs from other parties are less likely to do so (Poblete-Cazenave, 2020). However, this is only the case for criminal cases with non-serious criminal charges. There is no effect on serious criminal cases. Despite these concerns, the affidavit data remains the best possible source of information about politicians' criminal backgrounds and has been extensively used in the literature to study economic and political outcomes (Vaishnav, 2017; Prakash et al., 2019; Asher and Novosad, 2020).

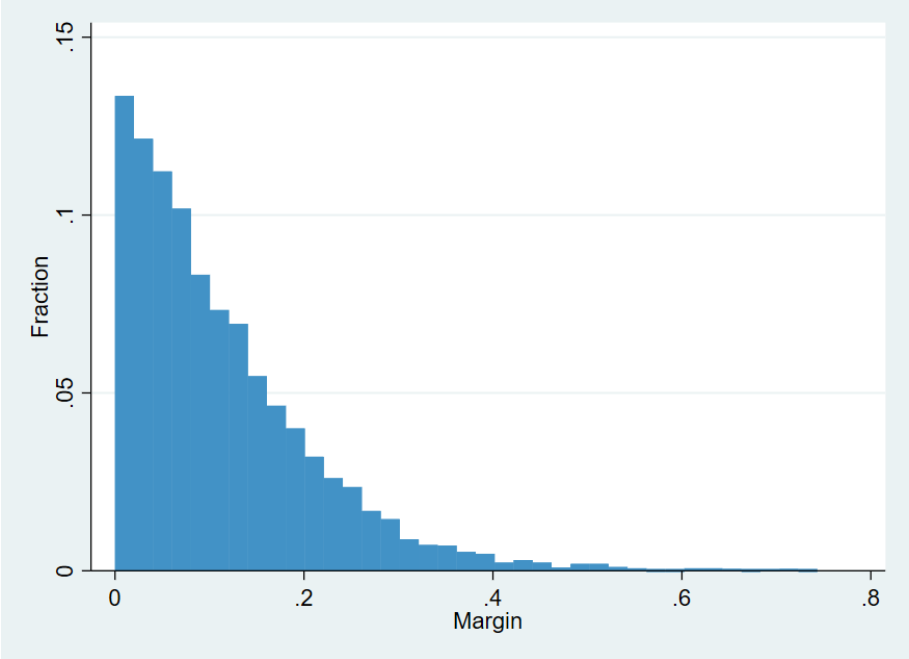
3.2.2.4 Electoral Results

Finally, I obtain electoral records data for each of the electoral races during this period, including information on turnout and results from the Lok Dhaba dataset compiled by the Trivedi Center of Political Data at Ashoka University (Bhogale et al., 2019). As a delimitation of constituencies took place in 2008, I restrict the time period under consideration to all elections in the post-delimitation period.

Since names of both constituencies and candidates are non-standardized, I match candidate records across the affidavit and electoral performance data using a fuzzy name matching process.[62] I only consider the criminal records of the winner and the runner-up in each of the electoral races, and exclude constituency-assembly periods where either the affidavit information of a winner or a runner-up is missing. States have had a minimum of two and a maximum of three elections during the period 2008-2019. A summary table with the number of constituencies, police stations and election periods can be seen in Table 3.B.1 in Appendix 3.B. Details of excluded states and union territories are included in Table 3.B.2 in Appendix 3.B.

In terms of electoral competitiveness, most races are close with a median margin of victory of 8.80%. Figure 3.1 presents the distribution of electoral races in my sample.[63]

Figure 3.1: Electoral Races are, On Average, Quite Competitive



Notes: The figure presents the distribution of the margin of victory in my sample. The margin of victory here is defined as the difference between the vote share of the criminal and the non-criminal, and is hence, always positive. The median margin of victory is 8.8%.

[62] I use the stata command 'reclink2' to undertake the preliminary matching, which I then verify manually for each match.

[63] Here, I define margin of victory as the difference between the vote shares of the winner and the runner-up. As a result, the margin of victory is always positive.

Because of the problem of non-overlapping boundaries (Alam, 2010), other key socio-economic aggregates, such population or income, are reported at higher administrative levels such as districts, or lower administrative units such as villages (rural) or wards (urban), and cannot be mapped to the police station jurisdiction. I combine the constituency-level data with information from the Socioeconomic High-resolution Rural-Urban Geographic panel for India (SHRUG) to obtain information on constituency-level socio-demographic characteristics such as population and literacy (Asher et al., 2019).

3.3 Empirical Methodology

To understand the causal impact of having a criminal politician in office on crime outcomes, it is insufficient to simply compare constituencies with elected criminals against those where non-criminals have been elected, as crime outcomes could be correlated with the election of a criminal politician to begin with. To account for unobserved differences in places where criminals and non-criminals are elected, I rely on close elections between criminals and non-criminals.[64] I also include fixed effects to account for time-invariant and police station-invariant characteristics that determine crime outcomes.

3.3.1 Regression Discontinuity Design

I use a close-election Regression Discontinuity (RD) design to evaluate the causal impact of having a criminal politician in elected office on crime in their constituency. Lee and Lemieux (2010) suggest that RD designs can be used to estimate treatment effects in a non-experimental setting where treatment or control status is assigned as a deterministic function of an observed covariate, which in this case is the margin

[64]Elections in this setting usually have multiple candidates, but in this study, I focus on the criminal records of the winner and the runner-up.

of victory. A positive margin of victory, no matter how small, results in a candidate being the winning political candidate in a given race. Yet, we expect that in races with very small margins of victory, whether a particular candidate won or lost is a matter of chance, thus resulting in variation of the treatment being 'as good as random' (Lee, 2008). This allows us to infer causal impact, in the form of a Local Average Treatment Effect (LATE) around the cut-off point of zero margin of victory.

Since the margin of victory deterministically assigns treatment or control status, the probability of treatment sharply jumps from 0 to 1 where the margin of victory is zero. Following the standard setup of a sharp RD design, I use the margin of victory ($Margin_j$) as the running variable, defined as follows.

$$Margin_j = Voteshare_{Criminal,j} - Voteshare_{Non-criminal,j}$$

$Criminal_j$, the assignment variable, takes the value 1 when the vote share of the criminal politician is higher than that of the non-criminal politician, and 0 otherwise.

$$Criminal_j = \begin{cases} 1 & Margin_j \geq 0 \\ 0 & Margin_j < 0 \end{cases}$$

By construction, $Margin_j$ is positive if the elected politician is a criminal, and negative when the elected politician is a non-criminal. I exclude all races where two criminals or two non-criminals run against each other. Equation 3.1 presents the RD estimation specification, where $Crime_{ij}$ represents the outcome measures of crime in police station i and constituency j. While the coefficients on the margin and interaction variables have no substantive interpretation, the coefficient on the assignment variable is the RD coefficient of interest, or the LATE.

I estimate the RD equations in two ways. First, I conduct a sharp RD without including any covariates (Equation 3.1). Second, in my preferred specification (Equation 3.2), I also include year and week fixed effects (γ_t) and police station fixed

effects (α_{ij}) as covariates in the RD estimation to control for any temporal variations and unobserved differences at the police station level. Following Cattaneo et al. (2019), these fixed effects are assumed to be predetermined, in that their values are determined prior to, or independently from, the treatment assignment, implying that the treatment effect on them is zero by construction. The inclusion of the fixed effects should not affect the validity of the LATE point estimate, while at the same time, improving its efficiency (Cattaneo et al., 2019).

$$Crime_{ijt} = \beta_0 + \beta_1 Criminal_{jt} + \beta_2 f(Margin_{jt}) + \beta_3 Criminal_{jt} * f(Margin_{jt}) + \epsilon_{ijt} \quad (3.1)$$

$$Crime_{ijt} = \beta_0 + \beta_1 Criminal_{jt} + \beta_2 f(Margin_{jt}) + \beta_3 Criminal_{jt} * f(Margin_{jt}) + \alpha_{ij} + \gamma_t + \epsilon_{ijt} \quad (3.2)$$

Following Gelman and Imbens (2019), I only use local linear or quadratic polynomials and do not use any higher-order polynomials for the RD estimation. The choice of bandwidth in a regression discontinuity design is a key parameter (Imbens and Kalyanaraman, 2012) and represents the trade-off between efficiency and bias. A very narrow bandwidth reduces the sample and hence affects statistical power, whereas a broad bandwidth could introduce bias as units on either side of the threshold become less comparable. I follow the data-driven bandwidth selection procedure given by Calonico, Cattaneo, and Titiunik (2014), which is an improvement over the bandwidth selection procedure specified by Imbens and Kalyanaraman (2012), to produce the main results in this paper. The mean squared error optimal bandwidth is calculated (Calonico, Cattaneo and Titiunik, 2014). Triangular kernel-weighted local linear estimates of the outcome variable are used in all the baseline estimates. Triangular kernel weights give more weight to observations closer to the cut-off (de la Cuesta and Imai, 2016). Finally, as recommended by Cattaneo et al. (2019) and in line with the most recent RD literature, I present conventional point estimates along with robust standard errors and robust p-values in the regression tables. This is because while the point estimate from the conventional bandwidth is consistent

and has minimal asymptotic mean-squared error, which makes it a highly desirable point estimator, using the same bandwidth for inference ignores the polynomial approximation bias and leads to invalid distributional approximations. Thus, robust standard errors and robust p-values are presented for inference.

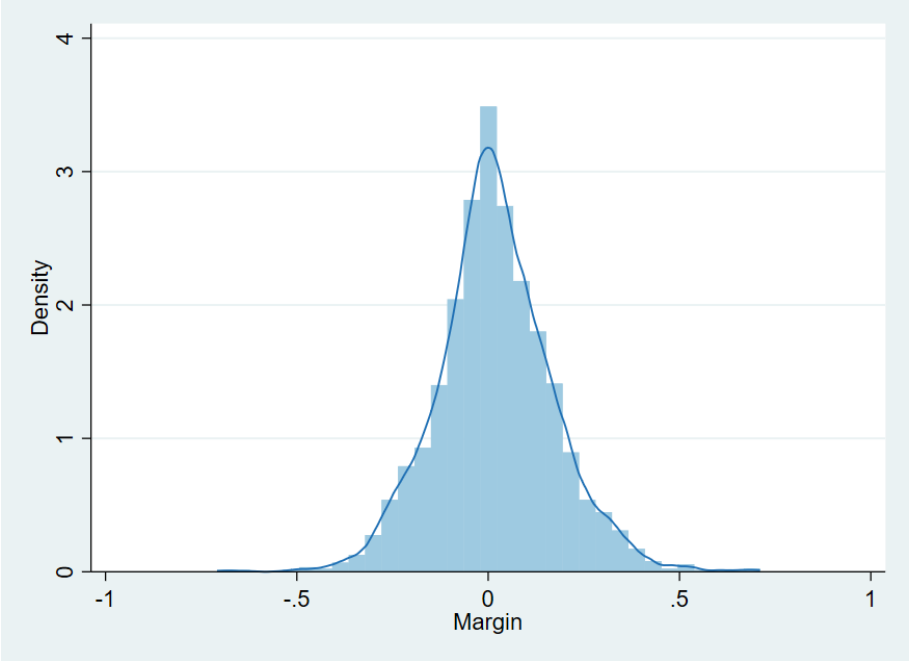
3.3.2 Validity of RD Design: Continuity, Balance Tests and Sorting

For valid inference, we require three identifying assumptions to hold. First, the running variable, which is the margin of victory, must be continuous at the zero threshold. The distribution of the running and assignment variables at the cut-off are as expected (Figures 3.2 and 3.3). Second, other relevant covariates must not be discontinuous at the threshold, so that those who barely won are comparable to those who have barely lost. This assumption can be econometrically and graphically tested. Tables 3.3 and 3.4 show that there are no discontinuities in the distribution of constituency and candidate characteristics.

I use a constituency-level dataset, merged with the SHRUG data, to demonstrate the smoothness of covariates, shown in Table 3.3. Most of the constituency characteristics in Table 3.3 are primarily derived from the decadal census, and remain constant for a constituency over the entire sample period.[65] In the case of nightlights, forest cover, turnout, and incumbency status, where multiple observations exist over the sample period, the number of observations is higher. All of the characteristics are continuous at the cut-off. Table 3.4 presents similar results for candidate characteristics. Candidate characteristics, such as their educational backgrounds, are observed at the constituency-assembly period level, for winners as well as runners-up. Most of the candidate characteristics, except for college education and party membership, are continuous at the cut-off. Appendix 3.E presents the results using education levels and party membership as the assignment variable and finds no

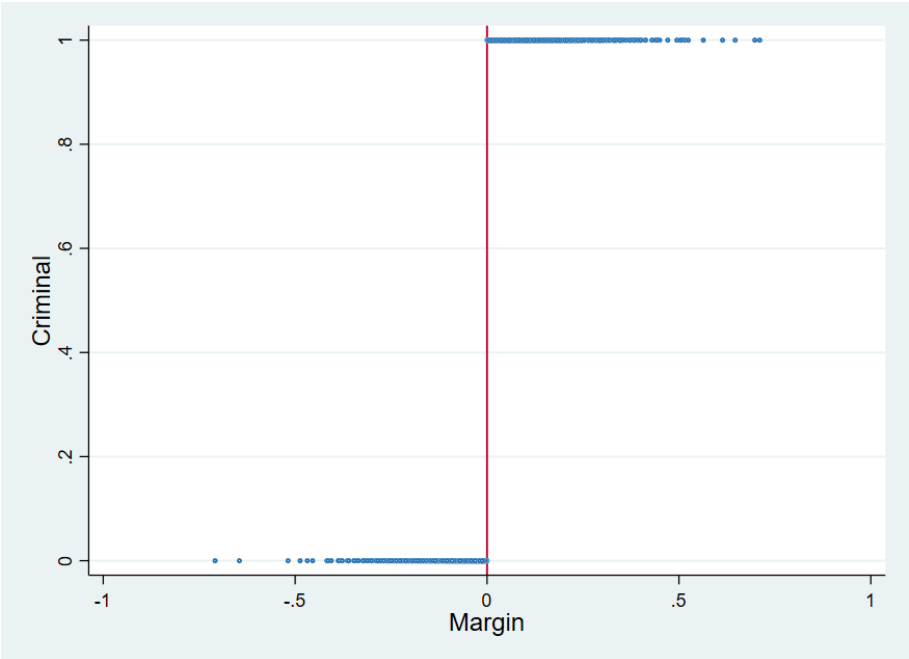
[65] I use the 2011 census values rather than the 2001 census values for the years 2008-2010 to avoid issues related to the delimitation, and since the years 2008-2010 are closer to 2011 compared to 2001.

Figure 3.2: The Running Variable, Margin, is Continuous at the Cut-off



Notes: The figure presents the distribution of the running variable, margin of victory. Margin of victory, here, is defined as the difference between the vote share of the criminal and the vote share of the non-criminal. Hence, it is positive when a criminal politician wins and negative otherwise. The univariate kernel density function is plotted using the Epanechnikov kernel function. As can be seen, the running variable is continuous at the cut-off margin of zero.

Figure 3.3: The Assignment Variable, Criminal, is Discontinuous at the Cut-off



Notes: The figure presents the distribution of the assignment variable, criminal. Criminal takes the value 1 if the margin of victory is greater than or equal to zero, and takes the value 0 when the margin of victory is negative. As can be seen, the assignment variable is discontinuous at the cut-off margin of zero.

impact of education levels or party membership on crime outcomes.

Table 3.3: Constituency Characteristics are Smooth at the Cut-off

Variable	**Difference**	**p-value**	**Observations**
Per capita consumption (Rs.)	-554.462	0.371	623
Agricultural households (%)	-0.030	0.216	629
Pre-period Serious IPC Count	-0.265	0.421	959
Literacy Rate	0.003	0.833	642
Share of Population Urban	0.045	0.168	642
SC/ST Share	-0.003	0.903	642
Number of households	2185.466	0.413	642
Total non-farm employment (2013)	563.807	0.823	623
Total non-farm employment (2005)	1845.190	0.343	570
Average Nightlights (2008)	3.369	0.125	908
Average Forest Cover (2008)	0.155	0.900	908
Area of town (sq.km.)	4.341	0.379	560
Number of senior secondary schools (T)	-0.745	0.634	560
Number of colleges (T)	1.339	0.171	560
Number of secondary schools (T)	1.046	0.672	560
Number of middle schools (T)	3.316	0.591	560
Number of primary schools (T)	7.221	0.306	560
Power supply for all users (%)	-0.044	0.313	638
Area of village (hectares)	3243.159	0.756	638
Accessibility by paved road	-0.018	0.563	638
Number of colleges (V)	-0.324	0.622	638
Number of senior secondary schools (V)	-0.462	0.800	638
Number of secondary schools (V)	-1.170	0.748	638
Number of middle schools (V)	-1.946	0.853	637
Number of primary schools (V)	9.480	0.642	638
Turnout (%)	-0.337	0.796	974
Incumbent (1/0)	-0.047	0.410	839

Notes: The table presents balance between treated and untreated units using the OLS specification at the optimal bandwidth. Difference represents the treatment effect of having a criminal politician on each of the outcome variables. Margin and the interaction of Criminal and Margin are included as controls. Standard errors are clustered at the constituency-assembly period level. (T) and (V) refer to town and village-level measures, respectively. All outcome variables are at the constituency level, except for turnout and incumbent, which are at the constituency-assembly period level. Agricultural households refers to households with main income from cultivation.

Finally, it must not possible for individuals to sort themselves into treatment and control. An extensive literature has used the RD design for causal inference in an election setting in India (Asher and Novosad, 2017; Nellis et al., 2016), and supports the claim that sorting is unlikely to occur in this context.[66] I use the McCrary test

[66]In addition, Eggers et al. (2015) study over 40,000 close elections in the world and find little evidence of systematic manipulation.

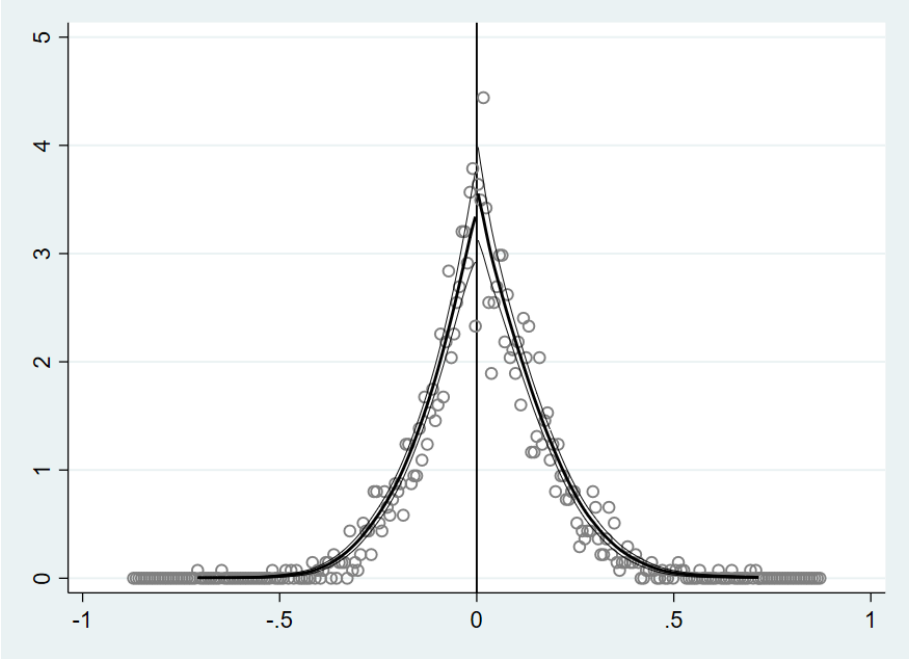
Table 3.4: Candidate Characteristics are Smooth at the Cut-off

Variable	**Difference**	**p-value**	**Obs.**
Male (1/0)	-0.032	0.119	1,950
Illiterate (1/0)	0.000	0.968	1,950
Primary Education (1/0)	0.012	0.374	1,950
Secondary Education (1/0)	0.018	0.660	1,950
College (1/0)	-0.071	0.061	1,950
Graduate, Graduate Professional or Doctorate (1/0)	0.027	0.515	1,950
Party = BJP	-0.080	0.008	1,950
Party = INC	-0.017	0.567	1,950
Party other than BJP/INC	0.097	0.032	1,950
Age	1.805	0.381	438
Total Assets (Rs. million)	11.334	0.358	1,950
Total Liabilities (Rs. million)	6.075	0.178	1,950
Effective Number of Parties	0.015	0.898	1,950
Number of Criminal Cases	0.298	0.275	1,950
Total IPC Violations	1.215	0.347	1,948
Total Serious IPC Violations	0.194	0.479	1,948

Notes: The table presents balance between treated and untreated units using the OLS specification at the optimal bandwidth of 0.085. Difference represents the treatment effect of having a criminal politician on each of the outcome variables. Margin and the interaction of Criminal and Margin are included as controls. Primary education refers to at most passing the 5th standard. Secondary education refers to at most passing the 8th, 10th, or 12th standards. College refers to at most going to college. Standard errors are clustered at the constituency-assembly period level.

(McCrary, 2008) to test for sorting, and do not find any evidence of it. Figure 3.4 presents the results of the McCrary test, and shows that there is no jump in the density of the distribution of the running variable around the threshold of zero. I also use the local polynomial regression based density estimation proposed in Cattaneo, Jansson and Ma (2020), and the results are shown in Figure 3.5.

Figure 3.4: There is No Evidence of Sorting of Winners (McCrary, 2008)

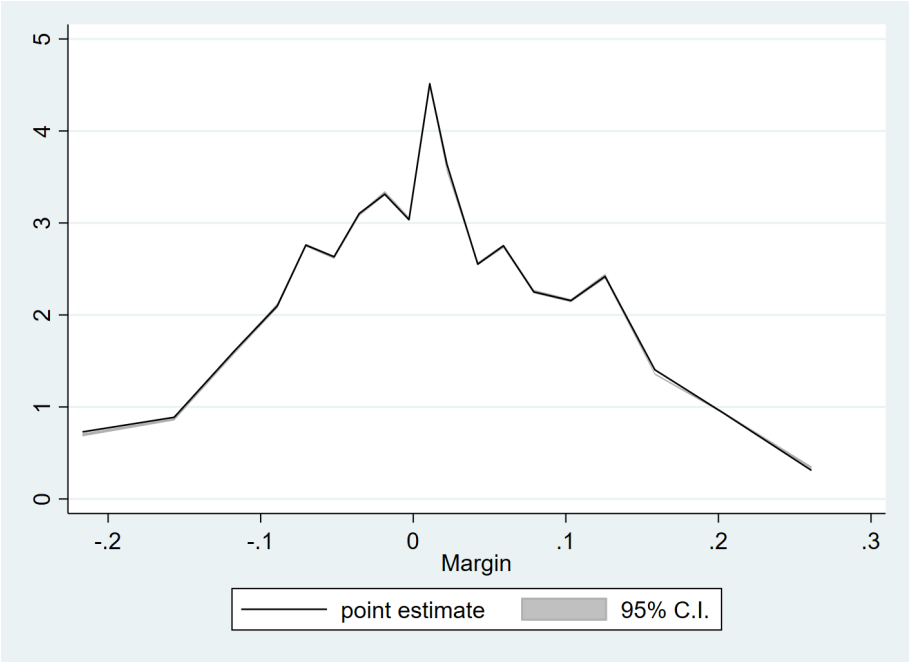


Notes: The figure presents the results from the McCrary Test to check if there is manipulation of the running variable. I use a constituency-assembly period dataset rather than the full panel dataset. The discontinuity estimate (log difference in height) is 0.063208445 with a standard error of 0.092324449.

3.4 Reported Reduction in Serious Crime

Having shown that the identifying assumptions of the regression discontinuity design hold, I now use the method to study the impact of electing a criminal politician to office on the nature and magnitude of local crime. Of the five main outcome variables defined above, there is a sharp and significant decline in the levels of serious crime in places with criminal politicians in office, as compared to places where non-criminals were narrowly elected. Violations count and crime count are also lower, and there is no significant difference in the case count (Table 3.6).

Figure 3.5: There is No Evidence of Sorting of Winners (Cattaneo, Jansson and Ma, 2020)



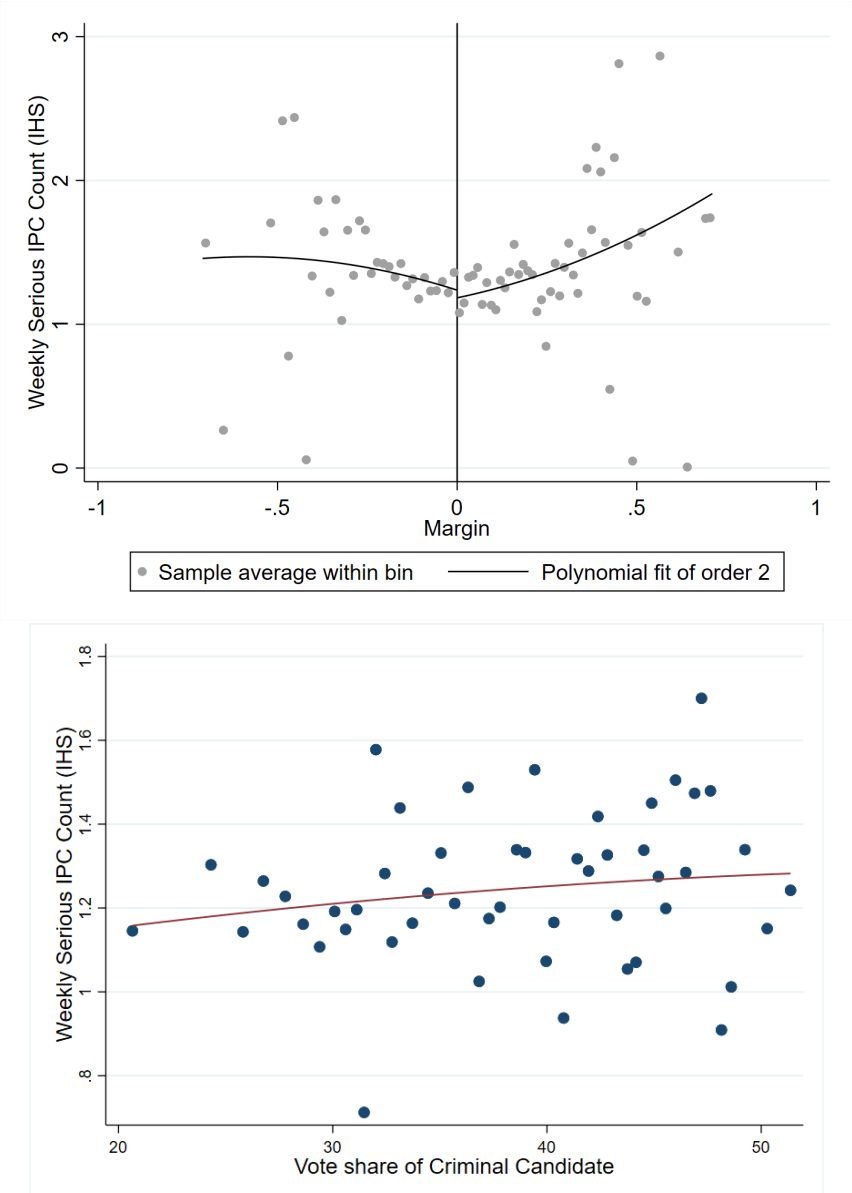
Notes: The figure presents the results from the local polynomial density estimation technique given by Cattaneo, Jansson and Ma (2020) and estimated using the stata command 'lpdensity'.

Column 1 of Table 3.5 presents the RD estimates from a local linear regression at the optimal bandwidth of serious crime. Column 2 includes time fixed effects at the week and year levels, Column 3 includes police station fixed effects. Column 4 represents the preferred specification used in the empirical analysis, and includes both time and police station fixed effects. The coefficient of serious IPC crimes is negative and significant, using linear polynomials over the optimal bandwidth, with and without the inclusion of fixed effects. Unless otherwise specified, the subsequent analysis in the main paper uses serious crimes as the main outcome variable, where conventional point estimates and robust p-values are presented; year, week, and police station fixed effects are included; standard errors are clustered at the constituency-assembly period level; triangular kernel-weighted local linear estimates are calculated; estimates are adjusted for mass points in the running variable; the dependent variable is transformed using the inverse hyperbolic sine transformation; and no other covariates are included.

These results show that places where a criminal politician narrowly won the electoral

race and was in office record 23.6 percent lower weekly serious crime as compared to places where a non-criminal politician was in office (preferred specification estimates in Column 4).[67]

Figure 3.6: Positive Relationship between Crime and Criminal Vote Share



Notes: The first figure presents a data-driven regression discontinuity plot, using evenly-spaced partitioning and a uniform kernel. Sample average within each bin and the global polynomial of best fit is plotted using the Stata command 'rdplot'. The second figure presents the serious IPC crime count (IHS) on the y-axis and vote share of the criminal on the x-axis in mixed races within the optimal bandwidth. The points represent average crime in 50 equally sized-bins, and a quadratic curve of best fit.

[67]The optimal bandwidth from this specification is 0.085. This bandwidth is used throughout the paper for consistency of the sample. However, results are robust to the calculation and use of optimal bandwidths. All regression tables from the main paper are replicated using optimal bandwidth estimation in Appendix 3.F.

Table 3.5: Impact of Criminal Politician on Weekly Serious Crime

Serious Crime Count	(1)	(2)	(3)	(4)
Criminal	-0.274	-0.268	-0.242	-0.236
Robust Std. Error	.112	.109	.108	.106
Robust p-value	.005	.005	.01	.011
Mean	1.268	1.269	1.278	1.281
Effect Size (%)	-21.6	-21.11	-18.94	-18.4
Bandwidth	.083	.083	.085	.085
Observations	1243461	1243461	1243461	1243461
Bandwidth obs.	614348	615556	627439	630085
Police Station FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
Week FE	No	Yes	No	Yes

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly serious IPC count. All estimates are derived from a sharp RD design with triangular kernel-weighted local linear estimates over the optimal bandwidth calculated using the Stata command 'rdrobust'. Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. The mean squared error optimal bandwidth is calculated following Calonico, Cattaneo and Titiunik (2014). Column 1 presents the RD estimates without inclusion of any other covariates or fixed effects. Column 2 includes time fixed effects. Column 3 includes police station fixed effects. Column 4 presents results including week, year, and police station fixed effects. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

There is a decline in the total violations of crime, as well as in weekly crime counts, consistent with the decline in serious crimes (Table 3.6). I find that there is no change in the total number of cases registered.[68] The results for the optimal bandwidth can be seen in Appendix Table 3.F.9. The decline in violation count and crime counts can be seen using both the optimal and the fixed bandwidths.

Table 3.6: Impact of Criminal Politician on Weekly Crime Outcomes

	(1) Cases	(2) Violations	(3) Crime Count	(4) Non-Penal Code
Criminal	-0.119	-0.249	-0.250	-0.0893
Robust Std. Error	.159	.197	.186	.117
Robust p-value	.123	.022	.025	.097
Mean	1.698	2.241	1.915	1.093
Effect Size (%)	-7.03	-11.09	-13.04	-8.17
Bandwidth	0.085	0.085	0.085	0.085
Observations	1251985	1251985	1251985	1251985
Bandwidth obs.	630479	630479	630479	630479

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on various crime outcomes. All estimates are derived from a sharp RD design with triangular kernel-weighted local linear estimates over a fixed bandwidth of 0.085, derived as the optimal bandwidth in the preferred specification. Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. Column 1 presents results for the total number of complaints registered. Column 2 presents results for the total number of crime violations. Columns 3 and 4 present results for the count of IPC and non-IPC violations, respectively. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the constituency-assembly period level. Week, year, and police station fixed effects are included. No other covariates are included.

What kinds of crimes are lower? As mentioned above, the IPC is composed of 26 chapters and over 511 sections that describe offences and prescribe punishment for a range of crimes committed against the human body, property, the state, public order, marriage, religion, and so on. Within the IPC, the substantive decline in crime is being driven a decrease in Chapter 5 (abetment), Chapter 9 (offences by or relating to public servants), Chapter 11 (of false evidence and offences against public justice), Chapter 16 (offences against the human body), Chapter 17 (property

[68]The change in the number of non-penal code violations is significant over the fixed bandwidth but not over the optimal bandwidth. I do not make any claims about the changes in non-penal code crimes in this paper.

crimes), Chapter 18 (offences relating to documents and to property marks), and Chapter 22 (offences related to criminal intimidation).[69] Chapters 16-18, associated with body and property-related crimes, are some of the most important chapters in the IPC, constituting over 50% of all IPC crimes. Table 3.7 summarizes the regression discontinuity estimates for each of the chapters in the IPC.

I further present evidence that the main result of the paper, the decline in serious crimes, is robust to various checks. I begin by showing that various choices of the specification of the regression discontinuity design, for example, using alternative bandwidths and kernel functions, do not alter the results. I then show robustness of the results to changes in the coverage of states, exclusion of outliers, inclusion of the election period, as well as changes in the clustering of standard errors. These results can be found in Appendix 3.G.

[69]There is also a decline in the incidence of crimes in Chapters 2 and 3, which refer to general explanations and the definition of punishments, respectively.

Table 3.7: Regression Discontinuity Estimates by IPC Chapter

Chp.	Description	RD Estimate	Robust p-value
1	Introduction	0.0005	.785
2	General Explanations	-0.1200	.035
3	Of Punishments	-0.0005	.075
4	General Exceptions	-0.0001	.709
5	Of Abetment	0.0157	.079
6	Of Offences against the State	0.0002	.143
7	Of Offences relating to the Army, Navy and Air Force	-0.0003	.388
8	Of Offences against the Public Tranquillity	-0.0288	.157
9	Of Offences by or relating to Public Servants	-0.0020	.049
10	Of Contempts of Lawful Authority of Public Servants	0.0095	.987
11	Of False Evidence and Offences against Public Justice	-0.0059	.005
12	Of Offences relating to coin and Government Stamps	-0.0001	.854
13	Of Offences relating to Weight and Measures	-0.0000	.661
14	Of Offences affecting the Public Health, Safety, Convenience, Decency and Morals	-0.0874	.251
15	Of Offences relating to Religion	-0.0020	.151
16	Of Offences affecting the Human Body	-0.1957	.032
17	Of Offences Against Property	-0.1549	.029
18	Offences relating to Documents and Property Marks	-0.0201	.021
19	Of the Criminal Breach of Contracts of Service	-0.0000	.621
20	Of Offences Relating to Marriage	-0.0014	.852
21	Of Defamation	-0.0012	.202
22	Of Criminal intimidation, Insult and Annoyance	-0.1311	.039
23	Of Attempts to Commit Offences	-0.0067	.111
5A	Criminal Conspiracy	-0.0094	.505
9A	Of Offences Relating to Elections	-0.0000	.958
20A	Of Cruelty by Husband or Relatives of Husband	-0.0163	.55

Notes: The table presents RD estimates of the impact of having a criminal politician in office on the weekly IPC count by chapter. All estimates are derived from a sharp RD design with triangular kernel-weighted local linear estimates using the Stata command 'rdrobust' over the fixed bandwidth of 8.5%. Conventional RD estimates and robust RD p-values are presented. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the constituency-assembly period level. Week, year, and police station fixed effects are included. No other covariates are included. Number of observations: 1251985. Number of observations in bandwidth: 630479.

3.5 Differences in Actual or Recorded Crime?

The evidence presented so far shows that the decline in serious crimes in areas where a criminal politician is elected into office is significant and robust. We know from the framework given by Donohue and Levitt (2001) and Iyer et al. (2012) that there are three steps in the crime process - the occurrence of crime, reporting by the victim, and recording by the police. Having a criminal politician in office could affect any or all three of these steps. I examine the role of reporting and recording in order to understand whether it is actual or reported crime that decreases. The decline in crime is only on the intensive margin (serious cases), there is no change on the extensive margin. The lower levels of serious recorded crime in criminal areas could be consistent with several explanations. Below, I put forward some of these explanations and provide evidence for them.

There are two main possibilities. First, the decline in cases in criminal areas could be a true decline in crime, under the assumption that serious crimes are often least likely to be under-recorded. Second, the decline in cases could reflect a decline in recording if police record less crimes in criminal areas as compared to non-criminal areas.[70] Under the assumption that serious crimes are least likely to be under-reported or under-recorded, the decline in crimes might reflect a true decrease in the occurrence of crime in criminal areas. This true decrease could be consistent with the explanation in Vaishnav (2017), that criminal politicians are elected not despite, but because of their criminal credentials and the ability to get things done in environments with weak rule of law. The decrease could also be consistent with a consolidation of criminal interests in the area post-election which reduces the 'need' for violence. On the other hand, the lower incidence of serious crimes could reflect a suppression of crime cases, if police record less crimes in criminal areas, that is, if the identity of the politician in charge matters more for crime recording than the

[70] A third possibility is that the difference could reflect a higher number of of serious cases in non-criminal areas, where criminal enforcement might be of higher quality.

nature or seriousness of the crime itself. To examine the effects of crime recording, I use information on murders and third-party reported data (from the media and from survey reports).

3.5.1 No Difference in Murders

Murders are often used to look at the true incidence of crime as they are least likely to be under-reported or under-recorded, since they are difficult to hide (Iyer et al., 2012). In a regression discontinuity regression, I find no significant reduction in weekly murders reported in police stations that come under criminal jurisdictions. The results are shown in Table 3.8. The effects are similar when optimal bandwidth results are calculated instead of using a fixed bandwidth of 8.5% (Table 3.F.11). These results show that even though there is a decline in the recorded incidents of crimes against the human body, there is no change in murders which are the most difficult crimes to hide.

Table 3.8: Impact of Criminal Politician on Weekly Murder

	(1) Murder
Criminal	-0.00482
Robust Std. Error	.005
Robust p-value	.313
Mean	.029
Effect Size (%)	-16.8
Bandwidth	0.085
Observations	1241248
Bandwidth obs.	627359

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly murder count. The dependent variable is transformed using the inverse hyperbolic sine transformation. The RD is conducted at the fixed bandwidth of 0.085 derived as the optimal bandwidth from the main results. Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. Standard errors are clustered at the constituency-assembly period level. Week, year and police station fixed effects are included. No other covariates are included.

3.5.2 No Difference in Political Violence

Similar to murders, which are difficult to hide, incidents involving political violence can also often be difficult to hide. The Armed Conflict Location and Events Data (ACLED) Project codes reported information from a wide range of local, regional and national sources on political violence, demonstrations (rioting and protesting) and select non-violent, politically important events (Raleigh et al., 2010). I use information on 59,745 events in India from the ACLED database over the duration 1 January 2016 - 31 December 2019. The project collects information on six types of events - battles, explosions/remote violence, violence against civilians, protests, riots and strategic developments, with further information on sub-event types within each of these categories. Table 3.9 presents the number of observations within each of the categories over the four-year period.

Table 3.9: Distribution of ACLED Data, 2016-2019

Event Type	Frequency	Share
Protests	43,810	73.33
Riots	8,711	14.58
Battles	3,304	5.53
Violence against Civilians	2,466	4.13
Explosions or Remote Violence	857	1.43
Strategic Developments	597	1.00
Total	**59,745**	**100.00**

Notes: The table presents the distribution of ACLED events in India over the period 1 January 2016 - 31 December 2019.

For this analysis, I exclude events that come under the categories of Battles, Explosions or Remote Violence and Strategic Developments, as these are not incidents that would typically be recorded as offences in the Indian Penal Code.[71] Using the

[71] As per ACLED, Battles includes the following sub-events - Armed clash, Government regains territory, and Non-state actor overtakes territory. The sub-events included within Explosions or Remote Violence are Chemical weapon, Air/drone strike, Suicide bomb, Shelling/artillery/missile attack, Remote explosive/landmine/IED, and Grenade. The sub-events within Strategic Developments (non-violent events) are Agreement, Arrests, Change to group/activity, Disrupted weapons use, Headquarters or base established, Looting/property destruction, Non-violent transfer of territory and Other.

geo-codes of the remaining 92.04% incidents in the data provided by ACLED, I map the incidents to the assembly constituencies that they are located in (DataMeet India, 2019), and aggregate the count of incidents at the constituency level. Column 1 of Table 3.10 presents the regression discontinuity results using the count of incidents recorded by ACLED, and I find no significant difference in the number of incidents or fatalities in constituencies that are controlled by criminal, rather than non-criminal, politicians.

For comparison, I show the results of a similar analysis, conducted at the police station level using the administrative crime data, over the same 2016-2019 period (Column 3 of Table 3.10). I restrict the administrative data to include only offences recorded under Chapter VIII of the IPC, pertaining to 'Offences against Public Tranquillity'. This includes offences related to unlawful assembly (for example, protests) and rioting.[72] The administrative crime data also shows no difference in offences related to protests and riots occurring in criminal areas. Column 4 presents the main result of the paper for the same time period. Together, we are unable to learn much from these results as there is no overall change in Chapter VIII of the IPC over the full sample period either.

3.5.3 No Difference in the Recording of Domestic Violence

In the absence of a national crime victimization survey, domestic violence is one of the rare crimes for which we have information on reporting of crime by victims to the police. I use information on the prevalence and reporting of domestic violence from the DHS (National Family Health Survey-4) conducted in India in 2015-16 (IIPS/India and ICF, 2017; ICF, 2018). I merge the DHS data with information on the political and criminal profile of the constituency at the constituency-month level.

[72]Chapter VIII is composed of sections 141-160, as well as sections 153A and 153B of the IPC.

Table 3.10: Impact on Political Violence

	(1) ACLED Count	(2) ACLED Fatalities	(3) NCRB Count	(4) IPC Serious
Criminal	-0.007	-0.001	-0.056	-0.239
Robust Std. Error	.017	.001	.057	.199
Robust p-value	.725	.284	.155	.183
Bandwidth	0.085	0.085	0.085	0.085
Observations	171203	171203	525829	522979
Bandwidth obs.	80015	80015	259381	258621
Unit FE	Constituency	Constituency	Police Station	Police Station
Year FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly levels of political violence, defined as protests, riots and violence against civilians. The dependent variables are transformed using the inverse hyperbolic sine transformation. Columns 1 and 2 presents results from a RD regression at the assembly constituency level with week, year and constituency fixed effects using the State 'rdrobust' command. Columns 3 and 4 present results from a RD regression at the police station level with week, year and police station fixed effects for the period 2016-2019. Conventional RD point estimates are presented along with robust RD standard errors and p-values. The dependent variables in columns 3 and 4 are IPC Chapter 8 (offences against public tranquillity) and serious IPC crimes. The period under consideration is 2016-2019, for which the ACLED data is available. All the regressions are conducted at the fixed bandwidth of 0.085 derived as the optimal bandwidth from the main results. Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

For the observations of constituency-month for which both domestic violence data and treatment information were available, I create two variables. Of all the women selected for the domestic violence module, I calculate the average percentage of women who have experienced domestic violence. Of all those who experienced domestic violence, I look at the average share of women who sought help from the police. Details of the calculation of these variables is given in Appendix 3.D.1. Table 3.11 shows that there is no difference in incidence of domestic violence and in the reporting of domestic violence to the police in criminal constituencies. The administrative data in Table 3.12 also shows no difference in the levels of domestic violence in criminal areas, including for the same period over which the DHS data was collected (Jan 2015 - Dec 2016). The DHS questions ask whether an individual has *ever* experienced domestic violence. In column 3 of Table 3.12, I look at recording of domestic violence in the entire period since the availability of administrative data until the end of the survey period, and again, find that there are no differences in the instances of recorded domestic violence in police stations that are a part of criminal constituencies.

The findings from the analyses using the ACLED and the DHS datasets are consistent with the main results in Table 3.7, where neither Chapter 8 on 'Public Tranquillity', nor Chapter 20A on 'Cruelty by Husbands or Relatives of Husbands' are significantly different in criminal and non-criminal areas to begin with.

3.5.4 No Difference in Crime Victimisation

Finally, I also use data on crime victimization from the India Human Development Survey-II (IHDS2) conducted in 2011-12 (Desai and Vanneman, 2018). The IHDS2 is a nationally representative survey of 42,152 households across India.

$$Crime_{dt} = \beta_0 + \beta_1 Criminal_{jdt} + \beta_2 Margin_{jdt} + \beta_3 Criminal_{jdt} * Margin_{jdt} + \gamma_t + \epsilon_{jdt} \quad (3.3)$$

Table 3.11: Relationship between Criminal Constituency and Domestic Violence

	(1) Experienced D.V.	(2) Sought Help from Police
Criminal	0.010	0.019
	(0.042)	(0.011)
Margin	0.395	-0.013
	(0.708)	(0.048)
Criminal*Margin	0.177	-0.390**
	(0.949)	(0.186)
Constant	0.294***	0.006*
	(0.033)	(0.003)
PS FE	No	No
Year FE	No	No
Week FE	No	No
Obs	446	399

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents simple OLS estimates of the impact of having a criminal politician in office on levels of domestic violence measured from DHS data. Observations are collapsed with weights to the constituency-month level for the sample period. Column 1 measures the share of women who experienced domestic violence as a percentage of all women selected for the domestic violence module of the DHS. Column 2 measures the share of women who sought help from the police as a percentage of all women who experienced domestic violence. The period under consideration is 2015-2016. Only observations for which the margin of victory is less than 8.5% are included. Robust standard errors are used. No other covariates are included.

Table 3.12: Impact of Criminal Politicians on Weekly Domestic Violence

	(1) Full Sample	(2) 2015m1-2016m12	(3) 2008m3- 2016m12
Criminal	-0.017	-0.018	-0.020
Robust Std. Error	.023	.023	.027
Robust p-value	.541	.778	.339
Bandwidth	.085	.085	.085
Observations	1241248	282903	860734
Bandwidth obs.	627359	143703	443063
Police Station FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly levels of domestic violence, defined as Section 498A of the IPC. The dependent variable is transformed using the inverse hyperbolic sine transformation. The period under consideration varies for the three columns. All the regressions are conducted at the fixed bandwidth of 0.085 derived as the optimal bandwidth from the main results. Conventional RD point estimates are presented along with robust RD standard errors and p-values. Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

The IHDS2 asks households whether there was a theft, break in, or if anyone in the household was attacked or threatened during the past 12 months. It also asks how often unmarried girls are harassed in the neighbourhood.[73] Since the IHDS2 has location information available only up to the district level, I aggregate this information using household weights to obtain district-level averages for a district d, and this measure is constant for all years prior to 2012. I exclude all observations after 2012 from the analysis. Since the victimization is only available as a cross-section, I do not include any fixed effects, except for year fixed effects. I restrict observations to constituencies with mixed races which had a close election with a margin less than or equal to the optimal bandwidth. These results suggest that there are fewer attacks in criminal areas and more harassment of women.

Table 3.13: Association between Crime Victimization

	(1) Theft	(2) Break In	(3) Attack	(4) Harassment
Criminal	-0.00786	-0.00460	-0.0123*	0.0730*
	(0.007)	(0.005)	(0.007)	(0.041)
Margin	0.0874	0.0460	0.169	-0.791
	(0.116)	(0.089)	(0.127)	(0.598)
Criminal*Margin	-0.0632	0.0208	-0.0768	-0.133
	(0.170)	(0.148)	(0.183)	(0.917)
Constant	0.0391***	0.00751*	0.0240***	0.121***
	(0.006)	(0.004)	(0.007)	(0.030)
Year FE	Yes	Yes	Yes	Yes
Observations	859	859	859	859

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents simple OLS regression estimates of the association between a criminal politician in office and crime victimization as per the IHDS2. The dependent variable is the average occurrence of the crime in a given district as per the IHDS2 household survey. Observations are restricted to constituencies with mixed races which had a close election with a margin less than or equal to the optimal bandwidth, prior to and including the year 2012. Year fixed effects are included. Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

Overall, the analysis of recording of crime in this context shows that there are no major differences in measures of violence as measured by murders, political vio-

[73] Further information on the IHDS2 questions can be found in Appendix 3.D.2.

lence, domestic violence, and crime victimization surveys. Yet, there is sharp and robust decrease in measures of serious crimes in criminal constituencies. This suggests that there may be additional under-recording of crime taking place in criminal constituencies, rather than lower levels of occurrence or reporting. These findings, however, are at best indicative, and any interpretation should be made with great caution. One of the key reasons for this caution is that the kind of crimes that we can measure using the third-party data, such as political violence or domestic violence, are not significantly lower in criminal constituencies to begin with, even as per the administrative data. Finally, while murders are an important measure of crime that in not under-recorded, there are limits to what we can extrapolate from the murder results. Overall, the analysis from the previous section suggests that under-recording of crime may be partly playing a role in driving the decline in serious crime.

3.6 Mechanisms

To further understand the source of the decline in crime, I examine the various heterogeneities related to the criminal profile, looking at the relationship between the kinds of crime committed by a politician and how that matters for the main results as well as for under-recording. In order to better understand the relationship between criminality and crime outcomes, I focus on the profile of criminality of the criminal politicians and look at two particular aspects - the seriousness of crimes, and the proximity between the crimes of the politicians and crimes recorded. These characteristics can help identify a better match between the crimes that a politician may be involved with and the kinds of crimes that change in magnitude. This analysis could help us understand what is driving the decline in recorded crime, thinking about the role of signalling and rent-seeking by politicians, in particular.

3.6.1 Types of Criminals: Politicians' Serious Crime

In this context, it is not very uncommon for criminal cases to be registered against politicians, who in the course of political activity are likely to run up against the working of the law and order machinery.

Of the 511 sections in the IPC, politicians in the sample have been accused of 476. The highest share of violations is of Section 147 (punishment for rioting). 39% of all politicians in the sample of criminal politicians have been accused of this section at least once.[74] For 17 of 476 sections, more than 10% of politicians in the sample have been accused of violating the section at least once. For the remaining 459 sections in the sample, less than 10% of all politicians in the sample have been accused of violating the section at least once.[75] As can be seen from Table 3.14, the majority of crimes are related to rioting and unlawful assembly, etc. Of the 17 most commonly violated sections, only 5 are categorized as 'serious' as per ADR (2014) and are highlighted below.

Theoretically, we might expect that criminals accused of 'serious' and 'non-serious' crimes are quite different in terms of their motives for affecting crime. I hence look at the impact of 'serious' criminal politicians and 'non-serious' criminal politicians distinctly. In Column 1 of Table 3.15, I consider only those politicians who are accused of crimes that are serious in nature. Following the definition of ADR (2014), I redefine the assignment and running variable to only include those criminal politicians who have serious cases against them. The assignment variable, $Criminal_{jt}$ takes the value 1 where the politician has been accused of a serious crime. Non-serious criminal politicians are excluded from this analysis. In Column 2 of Table 3.15, I redefine the assignment and running variable to only include non-serious criminal

[74]These % do not take into consideration the *number* of violations of a given section by any single individual.

[75]The same politician in a different assembly period is treated as a different politician, as politician identifiers are election-specific.

Table 3.14: Most Common IPC Crimes Committed by Politicians

Sec.	% Accused	Section Description
147	39%	Punishment for rioting
149	32%	Every member of unlawful assembly guilty of offence ... common object
323	30%	Punishment for voluntarily causing hurt.
506	29%	**Punishment for criminal intimidation**
143	25%	Punishment for being member of unlawful assembly
504	25%	Intentional insult with intent to provoke breach of the peace.
341	24%	Punishment for wrongful restraint.
353	24%	Assault or criminal force to deter public servant from discharge of duty
148	23%	Rioting, armed with deadly weapon
34	21%	Acts done by several persons in furtherance of common intention.
427	20%	Mischief causing damage to the amount of fifty rupees.
188	17%	Disobedience to order duly promulgated by public servant.
332	13%	**Voluntarily causing hurt to deter public servant from his duty**
420	12%	**Cheating and dishonestly inducing delivery of property**
324	12%	**Voluntarily causing hurt by dangerous weapons or means**
120	11%	Concealing design to commit offence punishable with imprisonment.
307	11%	**Attempt to murder**

Notes: The table presents a summary of the share of politicians in the sample who have been accused of committing different crimes. The sections highlighted in bold are considered to be serious crimes following the definition from ADR (2014). Politicians can be accused of more than one section.

politicians running against non-criminal politicians. In each case, I show that candidate and constituency characteristics are continuous at the cut-off and that there is no evidence of sorting. These tests of the identifying assumptions of the RD can be found in Appendix 3.H. A simple comparison of the RD coefficients suggests that the change in crime is greater in magnitude when comparing non-serious criminal politicians with non-criminal politicians, even though I do not test this.[76]

Table 3.15: Impact of Criminal Politician by Type on Weekly Serious Crime

	(1) SCP vs NCP	(2) NSCP vs NCP
Criminal	-0.164	-0.418
Robust Std. Error	.188	.197
Robust p-value	.078	.008
Mean	1.264	1.318
Effect Size (%)	-12.97	-31.68
Bandwidth	.085	.085
Observations	790462	346170
Bandwidth obs.	405840	173038

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly serious IPC count. Column 1 compares serious criminal politicians (SCP) with non-criminal politicians (NCP), and Column 2 compares non-serious criminal politicians (NSCP) with non-criminal politicians (NCP). The dependent variable is transformed using the inverse hyperbolic sine transformation. The RD is conducted at the fixed bandwidth of 0.085 derived as the optimal bandwidth from the main results. Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. Standard errors are clustered at the constituency-assembly period level. Week, year and police station fixed effects are included. No other covariates are included.

Furthermore, when I compare the impact of these two different groups of criminal politicians on murders, the robust RD estimates still suggest that there is no change in the incidence of murders in either type of constituency, which continues to indicate that the decrease in crime could be driven, at least partly, by reporting.[77]

[76] I consider the alternative approach to undertake sub-group analysis suggested by Carril et al. (2018), which uses propensity score matching to to create matched sub-groups based on observables and then re-runs the RD on these weighted sub-groups. In this case, however, we do not have a good understanding of the observable characteristics that predict a criminal status, and hence I do not use this method.

[77] As per the analysis using the optimal bandwidth, there is no change in serious crimes when comparing serious criminal politicians with non-criminal politicians, but there is still a significant decline of 41.6% when comparing non-serious criminal politicians with non-criminal politicians (Table 3.F.14). Furthermore, the decline in murders in the former case is significant, whereas the decline in murders in the latter case is not (Table 3.F.15).

Table 3.16: Impact of Criminal Politician by Type on Weekly Murder

	(1) SCP vs NCP	(2) NSCP vs NCP
Criminal	-0.00877	-0.00153
Robust Std. Error	.007	.007
Robust p-value	.359	.125
Mean	.031	.025
Effect Size (%)	-28.45	-6.16
Bandwidth	.085	.085
Observations	788979	345691
Bandwidth obs.	404859	172787

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly murder count. Column 1 compares serious criminal politicians (SCP) with non-criminal politicians (NCP), and Column 2 compares non-serious criminal politicians (NSCP) with non-criminal politicians (NCP). The dependent variable is transformed using the inverse hyperbolic sine transformation. Week, year and police station fixed effects are included. The RD is conducted at the fixed bandwidth of 0.085 derived as the optimal bandwidth from the main results Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. Standard errors are clustered at the constituency-assembly period level. Week, year and police station fixed effects are included. No other covariates are included.

However, the comparison of changes in various IPC chapters coming from the two alternative types of criminal politicians shows that there are several important differences in the sources of decline in crime. RD estimates show that there is an increase in crimes related to abetment and offences against the state in areas where serious criminal politicians are elected, compared to non-criminal politicians. Serious criminal politicians reduce crimes against public servants and against religion, but have no impact on crimes against the body or property. On the other hand, non-serious criminal politicians reduce crimes against body, property, public tranquillity, and offences of defamation and criminal intimidation. Both reduce crime against public justice and property marks. These results show that there are differences in the kinds of crimes that serious and non-serious criminal politicians impact. They suggest that there might be different motives behind the crime reduction in these two groups, as crimes against body and property are likely to affect citizen security and safety, whereas crimes against religion are more likely to political in nature. A reduction in crimes against religion could reflect a consolidation of gains by

criminals and politicians, who often use religious crimes to strengthen their support base in this context. This would be in line with the suggestion of Vaishnav (2017) that criminal politicians have a reputation of being able to safeguard the interests of their groups against other groups and communities. However, this is not the case in places where non-serious criminal politicians are elected.

Table 3.17: Impact of Criminal Politician by Type on Weekly IPC Chapter Count

		SCP vs NCP		**NSCP vs NCP**	
Chp.	**Offences Against**	Criminal	Robust p-value	Criminal	Robust p-value
2	General Explanations	-0.0633	.317	-0.2280	.007
3	Punishments	-0.0006	.224	-0.0002	.332
5	Abetment	0.0169	.031	0.0021	.708
6	State	0.0003	.084	0.0004	.322
8	Public Tranquillity	-0.0291	.626	-0.0776	.005
9	Public Servants	-0.0013	.07	-0.0007	.344
11	Public Justice	-0.0077	.036	- 0.0046	.008
15	Religion	-0.0036	.072	0.0005	.733
16	Human Body	-0.1238	.253	-0.4052	.007
17	Property	-0.1198	.104	-0.2959	.003
18	Property Marks	-0.0224	.02	-0.0197	.08
21	Defamation	-0.0008	.538	-0.0019	.059
22	Criminal intimidation	-0.0533	.353	-0.2753	.041
23	Attempts to Offences	-0.0083	.077	-0.0093	.208
5A	Criminal Conspiracy	-0.0151	.348	-0.0105	.072
20A	Cruelty by Husband	-0.0009	.766	-0.0477	.154

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly IPC count by chapter. Column 3-5 compare serious criminal politicians (SCP) with non-criminal politicians (NCP), and Columns 6-8 compare non-serious criminal politicians (NSCP) with non-criminal politicians (NCP). The dependent variable is transformed using the inverse hyperbolic sine transformation. The RD is conducted at the fixed bandwidth of 0.085 derived as the optimal bandwidth from the main results. Conventional RD estimates and robust p-values are presented. Standard errors are clustered at the constituency-assembly period level. Week, year and police station fixed effects are included. No other covariates are included. Serious Criminal Politicians vs Non-Criminal Politicians: Bandwidth 0.085. Observations 795394. Bandwidth observations 406996. Non-Serious Criminal Politicians vs Non-Criminal Politicians: Bandwidth 0.085. Observations 348118. Bandwidth observations 173770.

It is important to note that the results on the impact on murder suggest that both serious and non-serious criminals reduce reporting. However, non-serious criminals may be doing so in order to signal performance on crime, whereas serious criminals may do so in order to also consolidate and safeguard their own rent-seeking interests, for example, by protecting their associates.

3.6.2 Types of Crimes: Politician's Own Crime

To look at the role of rent-seeking, I look at the role of a politician's specific criminal background on crime. The goal is to understand what happens not to crime in general, but the specific kinds of crime that a politician is himself accused of. For example, what happens to kidnapping in a constituency where a politician accused of kidnapping is elected? I undertake this analysis at the chapter level (for example, crimes against the human body), rather than at the section level (for example, kidnapping). With over 500 sections of the IPC, and over 200 sections of 'serious' IPC crimes, going over each of the sections one by one is likely to lead to problems of insufficient power. These sections are combined into various IPC chapters which I use to keep the analysis consistent. I aggregate the sections of the IPC to the chapter level. For each police station-week observation, I have information on the total number of crimes committed for a given chapter. I combine this with information on whether the politician in power in the relevant constituency is accused of a crime in chapter c as well.

$$Crime_{ijct} = \beta_0 + \beta_1 Criminal_{jt} + \beta_2 Margin_{jt} + \beta_3 Criminal_{jt} * Margin_{jt} + \beta_4 OwnCrime_{jct} * Criminal_{jt} + \alpha_{ijt} + \epsilon_{ijct} \quad (3.4)$$

$Crime_{ijct}$ is the crime level at time t in police station i in constituency j for chapter c, and $OwnCrime_{jct}$ is a dummy variable capturing whether the politician in power at time t in constituency j is accused of a crime in chapter c.

The results show that the specific criminal background of the politician matters. For example, having a criminal politician in office reduces property crimes (Chapter 17) by 15.4% overall (see Table 3.7). When the variable $OwnCrime_{jct} * Criminal_{jt}$ is included in the analysis, the coefficient of $Criminal_{jt}$ decreases further to 18.4%, and remains significant. In addition, the coefficient of $OwnCrime_{jct} * Criminal_{jt}$ is positive and significant at 7.4%.

Table 3.18: Impact of Criminal Politician's Own Crime on Weekly IPC Chapter Count

IPC Chapter	(1) Public Servants	(2) Religion	(3) Property	(4) Prop. Marks	(5) Attempts
Criminal	0.004**	-0.002**	-0.184***	-0.015*	-0.008***
	(0.002)	(0.001)	(0.056)	(0.009)	(0.003)
Criminal*Own Crime	-0.002*	-0.005***	0.074**	0.028**	-0.006**
	(0.001)	(0.001)	(0.034)	(0.012)	(0.003)
Police Station FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Obs	630389	630389	630389	630389	630389

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office and the impact of the criminal being accused of a particular chapter on the weekly count of that chapter of crime. The dependent variable is transformed using the inverse hyperbolic sine transformation. Chapter 9: Offences by or relating to Public Servants. Chapter 15: Offences relating to Religion. Chapter 17: Offences against Property. Chapter 18: Offences relating to Documents and Property Marks. Chapter 23: Attempts to Commit Offences. The estimates are produced using using a fixed effects regression at the police station level, with time fixed-effects using the Stata command 'reghdfe'. Mixed races within the optimal bandwidth of 0.085 are included. Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

This analysis suggests that in some domains of the law, such as when it comes to crimes against property, having a criminal politician in office who has been previously accused of a crime from that domain could matter. While the RD coefficient, $Criminal$ remains significant, the coefficient of $OwnCrime * Criminal$ matters as well. Criminals who have a background in property crimes (Chapters 17 and 18) are associated with higher property crimes relative to other criminals, as they safeguard their own interests. On the other hand, those accused of crimes against religion are associated with lower levels of those crimes compared to other criminals, perhaps as consolidation of politicians' interests takes place, 'reducing' the 'need' for further crimes against religion, for example, or as a signal of their ability to safeguard those from their own community. This is once again in line with the role of rent-seeking motivations in driving the reduction in crime.

3.6.3 Other Mechanisms

I also test several alternative mechanisms that could explain these results, and show that they do not matter. I look at the role of networks, authority, and information.

To test the role of authority, I compare the impact of criminal parliamentarians on crime, relative to the impact of criminal state legislators, as the latter have direct control over the functioning of the police. To test the role of networks, I test whether the impact is different for places where the state has a criminal Chief Minister in the state from the same party as the state legislator. In the case of information, criminal politicians might have had more interactions with the law and order machinery, as compared to non-criminal politicians, and this might be associated with effectiveness in reducing crime. For example, politicians who have been charged with a greater number of cases, or have been in the system for longer, or have been in office for a greater number of terms, might be better able to control the police, compared to those with less information about how the system works. These analyses can be

found in Appendix 3.I. The results suggest that none of these factors seem to be driving the results.

3.7 Conclusion

This paper studies the impact of politicians who are accused of committing crime on the nature and magnitude of local crime in their constituencies. It does so by undertaking a regression discontinuity analysis, and finds causal evidence of lower levels of recorded crime in areas where a criminal politician was narrowly elected into office. This decline in serious kinds of crime is robust to changes in the RD specification, as well as changes in coverage and timing of the analysis. Using data from other sources, including data on political violence, domestic violence, crime victimization, as well as using the incidence of murders, which are least likely to be under-recorded, I provide suggestive evidence that these changes are, at least partly, driven by lower levels of recording of crime in criminal constituencies.

To further understand the mechanisms at play, I look at the specific nature of the politician's criminal background. I study two aspects of criminal background – first, how 'serious' or 'non-serious' the accusations are, and second, whether the specific crimes that politicians are accused of change. The findings suggest that the kind of criminal profile that politicians have matters - 'non-serious' criminals decrease crime in categories such as body, property, and intimidation-related offences, where 'serious' criminals have no impact on these categories. Instead, they decrease crimes against public servants and crimes against religion, in line with a consolidation of criminal and political gains. Further, politicians' own criminal profile (for example, whether they are accused of committing crimes against property or religion) also affects the incidence of *those specific kinds* of crimes. These findings are consistent with alternative motivations for politicians' reduction of crime, including the role of signalling performance to constituents, and the role of rent-seeking once in office.

This research contributes to our understanding of the relationship between crime and politics in the developing world. However, several questions remain. We do not know whether the selection of criminal politicians into office is driven by adverse selection (criminals entering politics) or moral hazard (politicians engaging in crime). This could have important implications for the mechanisms through which criminal politicians affect crime. Second, improved monitoring of police recording of crime could impact the levels of suppression of crime, and remains an important area of investigation in future work. Finally, we know very little about criminality in politics at the local level, which is seen as being more widespread. This constitutes an important area of future work to further our understanding of crime, policing and politics in developing countries.

References

Ahmed, Hamna, Dareen Latif, and Kate Vyborny, "The Unintended Consequences of Political Accountability: Quasi-experimental Evidence from Policing in Pakistan," November 2021.

Aidt, Toke, Miriam A. Golden, and Devesh Tiwari, "Incumbents and Criminals in the Indian National Legislature," Mimeo., University of California-Los Angeles 2013.

Alam, Mohd Sanjeer, "On Matching Census Tracts and Electoral Boundaries: The Bottom-up Aggregation Approach," *Economic and Political Weekly*, 2010, *45* (34), 64–72.

Asher, Sam and Paul Novosad, "Politics and Local Economic Growth: Evidence from India," *American Economic Journal: Applied Economics*, 2017, *9* (1), 229–273.

_ **and** _ , "Rent-Seeking and Criminal Politicians: Evidence from Mining Booms," Working Paper. 2020.

_ **, Tobias Lunt, Ryu Matsuura, and Paul Novosad**, "The Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG)," 2019.

Association for Democratic Reforms, "Criteria for Categorization of Serious Criminal Cases," 2014.

_ , "Analysis of Chief Ministers from 29 State Assemblies and 2 Union Territories of India," February 2018, p. 28.

_ , "MyNeta Candidate Affidavits for Elections in India," 2021.

Barnes, Nicholas, "Criminal Politics: An Integrated Approach to the Study of Organized Crime, Politics, and Violence," *Perspectives on Politics*, December 2017, *15* (4), 967–987. Publisher: Cambridge University Press.

Berenschot, Ward, "On the Usefulness of Goondas in Indian Politics: 'Money-power' and 'Musclepower' in a Gujarati Locality," *South Asia: Journal of South Asian Studies*, August 2011, *34* (2), 255–275.

Bhogale, Saloni, Sudheendra Hangal, Francesca Refsum Jensenius, Mohit Kumar, Chinmay Narayan, Basim U Nissa, and Gilles Verniers, "TCPD Indian Elections Data v1," 2019.

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik, "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 2014, *82* (6), 2295–2326.

Carril, Alvaro, Andre Cazor, Maria Paula Gerardino, Dina Pomeranz, and Stephan Litschig, "Subgroup Analysis in Regression Discontinuity Designs," 2018.

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma, "Simple Local Polynomial Density Estimators," *Journal of the American Statistical Association*, July 2020, *115* (531), 1449–1455. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/01621459.2019.1635480.

_ **, Nicolas Idrobo, and Rocio Titiunik**, "A Practical Introduction to Regression Discontinuity Designs: Foundations," *arXiv:1911.09511 [econ, stat]*, November 2019. arXiv: 1911.09511.

Census of India, "Population and Decadal Change by Residence: 2011 (Persons)," Technical Report, Office of the Registrar General & Census Commissioner, New Delhi, India 2011.

Chemin, Matthieu, "Welfare Effects of Criminal Politicians: A Discontinuity-Based Approach," *The Journal of Law & Economics*, 2012, *55* (3), 667–690.

DataMeet India, "India Boundary Shapefiles," 2019.

de la Cuesta, Brandon and Kosuke Imai, "Misunderstandings About the Regression Discontinuity Design in the Study of Close Elections," *Annual Review of Political Science*, 2016, *19*, 375–396.

Desai, Sonalde and Reeve Vanneman, "India Human Development Survey-II (IHDS-II) (ICPSR 36151) [dataset and codebook]," August 2018.

Eggers, Andrew C, Anthony Fowler, Jens Hainmueller, Andrew B Hall, and James M Snyder, "On the Validity of the Regression Discontinuity Design for Estimating Electoral Effects: New Evidence from Over 40,000 Close Races," *American Journal of Political Science*, 2015, *59* (1), 259–274.

Fisman, Raymond, Florian Schulz, and Vikrant Vig, "The Private Returns to Public Office," *Journal of Political Economy*, 2014, *122* (4), 806–862.

Gehring, Kai, T. Florian Kauffeldt, and Krishna Chaitanya Vadlamannati, "Crime, incentives and political effort: Evidence from India," *European Journal of Political Economy*, September 2019, *59*, 1–20.

Gelman, Andrew and Guido Imbens, "Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs," *Journal of Business & Economic Statistics*, 2019, *37* (3), 447–456.

Global Initiative Against Transnational Organized Crime, "Global Organized Crime Index 2021: India Profile," Technical Report, Geneva, Switzerland 2021a.

_ , "Global Organized Crime Index 2021," Technical Report, Geneva, Switzerland 2021b.

Gulzar, Saad and Benjamin J. Pasquale, "Politicians, Bureaucrats, and Development: Evidence from India," *American Political Science Review*, February 2017, *111* (1), 162–183.

ICF, "Demographic and Health Surveys Standard Recode Manual for DHS7," Technical Report, Rockville, Maryland, USA 2018.

III, John J. Donohue and Steven D. Levitt, "The Impact of Race on Policing and Arrests," *The Journal of Law & Economics*, 2001, *44* (2), 367–394.

Imbens, Guido and Karthik Kalyanaraman, "Optimal Bandwidth Choice for the Regression Discontinuity Estimator," *The Review of Economic Studies*, 2012, *79* (3), 933–959.

International Institute for Population Sciences - IIPS/India and ICF, "India DHS, 2015-16 [Dataset]," 2017.

Iyer, Lakshmi, Anandi Mani, Prachi Mishra, and Petia Topalova, "The Power of Political Voice: Women's Political Representation and Crime in India," *American Economic Journal: Applied Economics*, 2012, *4* (4), 165–193.

Lee, David S., "Randomized experiments from non-random selection in U.S. House elections," *Journal of Econometrics*, 2008, *142* (2), 675–697.

Lee, David S and Thomas Lemieux, "Regression Discontinuity Designs in Economics," *Journal of Economic Literature*, June 2010, *48* (2), 281–355.

McCrary, Justin, "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of Econometrics*, February 2008, *142* (2), 698–714.

Michelutti, Lucia, Ashraf Hoque, Nicolas Martin, David Picherit, Paul Rollier, Arild E. Ruud, and Clarinda Still, *Mafia Raj: The Rule of Bosses in South Asia*, Redwood City, United States: Stanford University Press, 2018.

Ministry of Home Affairs, Government of India, "Vohra Committee Report," Technical Report 1993.

Murray, Galen, "Do Criminal Politicians Deliver? Evidence from India's Employment Guarantee and Hindu Holidays." Ph.D., University of California, Los Angeles, United States – California 2020. ISBN: 9798557038454.

Nanda, Vikram and Ankur Pareek, "Do Criminal Politicians affect Firm Investment and Value? Evidence from a Regression Discontinuity Approach," 2019.

National Crime Records Bureau, "Crime in India 2019," Technical Report, National Crime Records Bureau, Ministry of Home Affairs, New Delhi, India 2019.

Nellis, Gareth, Michael Weaver, and Steven Rosenzweig, "Do Parties Matter for Ethnic Violence? Evidence From India," *Quarterly Journal of Political Science*, 2016, *11* (3), 249–277.

Olson, Mancur, "Dictatorship, Democracy, and Development," *The American Political Science Review*, 1993, *87* (3), 567–576.

Poblete-Cazenave, Rubén, "Political Power and Judicial discretion," Working Paper. 2020.

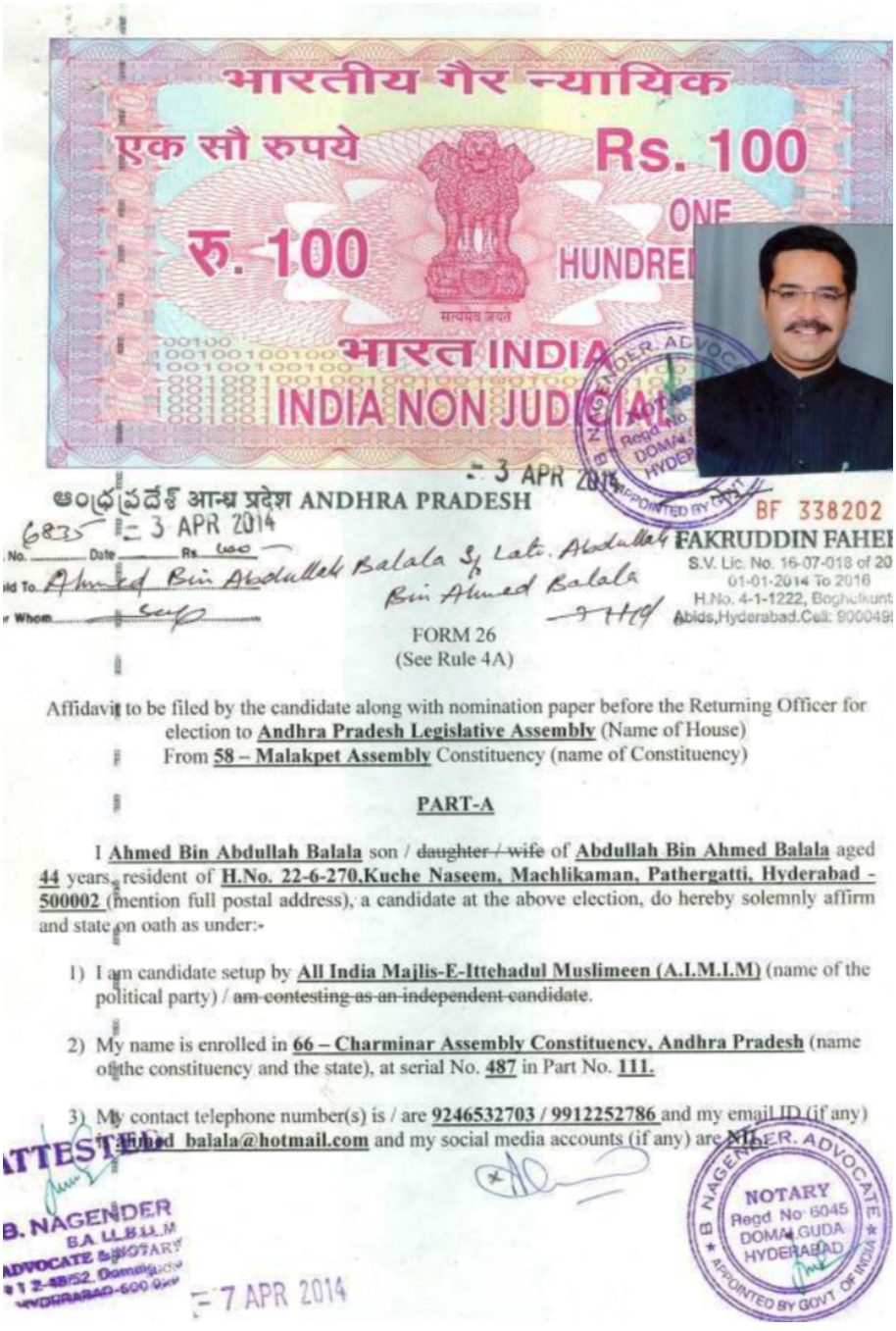
Prakash, Nishith, Marc Rockmore, and Yogesh Uppal, "Do Criminally Accused Politicians Affect Economic Outcomes? Evidence from India," *Journal of Development Economics*, November 2019, *141*, 102370.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen, "Introducing ACLED-Armed Conflict Location and Event Data," *Journal of Peace Research*, 2010, *47* (5), 651–660.

Vaishnav, Milan, *When Crime Pays: Money and Muscle in Indian Politics*, New Haven: Yale University Press, 2017.

Wilkinson, Steven, *Votes and Violence: Electoral Competition and Ethnic Riots in India* Cambridge Studies in Comparative Politics, Cambridge: Cambridge University Press, 2004.

3.A Example of a Candidate Affidavit



भारतीय गैर न्यायिक

एक सौ रुपये Rs. 100

रु. 100 ONE HUNDRED

सत्यमेव जयते

भारत INDIA

INDIA NON JUDICIAL

- 3 APR 2014

आन्ध्रप्रदेश आन्ध्र प्रदेश ANDHRA PRADESH BF 338202

6835 - 3 APR 2014

No. Date Rs. 100

Id To. Ahmed Bin Abdullah Balala S/o Late. Abdullah Bin Ahmed Balala

For Whom

FAKRUDDIN FAHE

S.V. Lic. No. 16-07-013 of 20
01-01-2014 To 2016
H.No. 4-1-1222, Boghalkunt
Abids,Hyderabad.Cell: 900049

B. NAGENDER, ADVOCATE, Regd No DOM/4 HYDER... APPOINTED BY GOVT

FORM 26
(See Rule 4A)

Affidavit to be filed by the candidate along with nomination paper before the Returning Officer for election to **Andhra Pradesh Legislative Assembly** (Name of House)
From **58 – Malakpet Assembly** Constituency (name of Constituency)

PART-A

I **Ahmed Bin Abdullah Balala** son / ~~daughter / wife~~ of **Abdullah Bin Ahmed Balala** aged **44** years, resident of **H.No. 22-6-270,Kuche Naseem, Machlikaman, Pathergatti, Hyderabad - 500002** (mention full postal address), a candidate at the above election, do hereby solemnly affirm and state on oath as under:-

1) I am candidate setup by **All India Majlis-E-Ittehadul Muslimeen (A.I.M.I.M)** (name of the political party) / ~~am contesting as an independent candidate~~.

2) My name is enrolled in **66 – Charminar Assembly Constituency, Andhra Pradesh** (name of the constituency and the state), at serial No. **487** in Part No. **111.**

3) My contact telephone number(s) is / are **9246532703 / 9912252786** and my email ID (if any) is / are **Ahmed_balala@hotmail.com** and my social media accounts (if any) are **NIL.**

ATTESTED
B. NAGENDER
B.A. LL.B., L.L.M.
ADVOCATE & NOTARY
1-2-48/52, Domalguda
HYDERABAD-500 029

- 7 APR 2014

B. NAGENDER, ADVOCATE
NOTARY
Regd No 6045
DOM/4 GUDA
HYDERABAD
APPOINTED BY GOVT OF INDIA

Figure 3.A.1: Sample Affidavit

(i) The Following case(s) are pending against me in which charges have been framed by the court for an offence punishable with imprisonment for two years or more:

A) a.	Case/First Information Report No./Nos. together with complete details of concerned Police Station/District/State	Crime No. 145 of 2006 and C.C. No. 18 of 2012 Kanchikacherla Police station Krishna District, Andhra Pradesh
b.	Section (s) of the concerned Act (s) and short description of the offence (s) for which charged	Under Section 147 and 188 of Indian Penal Code, Rioting and Disobedience to an order lawfully promulgated by a public servant
c.	Name of the Court, Case No. and date of order taking cognizance:	Principal Junior Civil Judge, Nandigama
d.	Court (s) which framed the charge (s)	Principal Junior Civil Judge, Nandigama CC No:18/2012 date 20.07.2007
e.	Date on which the charge (s) was/were framed	12-07-2007
f.	Whether all or any of the proceeding (s) have been stayed by any Court (s) of Competent Jurisdiction	Not applicable

B) a.	Case/First Information Report No./Nos. together with complete details of concerned Police Station/District/State	Crime No. 73 of 2011 Reddy Gudem Police station, Krishna District, Andhra Pradesh
b.	Section (s) of the concerned Act (s) and short description of the offence (s) for which charged	Under Section 353, 341, 143, r/w 149 of Indian Penal Code, and section 32 of A.P.Police Act. Obstructing the Government servant from discharging the duties



Figure 3.A.2: Sample Affidavit of a Candidate with Details of Crime Charges

3.B State Summaries

Table 3.B.1: Summary of States, 2008-2019

Type	State	#Constituencies	#Police Stations	#Elections
State	Andhra Pradesh	175	875	2
State	Arunachal Pradesh	60	76	2
State	Assam	126	317	2
State	Chhattisgarh	90	431	3
State	Goa	40	40	2
State	Gujarat	182	681	2
State	Haryana	90	331	2
State	Himachal Pradesh	68	149	2
State	Jammu and Kashmir	87	225	2
State	Jharkhand	81	497	2
State	Karnataka	224	1049	3
State	Kerala	140	536	2
State	Madhya Pradesh	230	1061	3
State	Maharashtra	288	1145	2
State	Manipur	60	78	2
State	Mizoram	40	42	3
State	Nagaland	60	62	3
State	Punjab	117	427	2
State	Rajasthan	200	894	3
State	Sikkim	32	28	2
State	Tamil Nadu	234	1531	2
State	Telangana	119	758	3
State	Uttar Pradesh	403	1542	2
State	Uttarakhand	70	157	2
UT	Delhi	70	244	3
UT	Pondicherry	30	45	2

Notes: The table summarizes the number of assembly constituencies, police stations and elections for each of the 26 states and union territories included in the sample. Some states held their most recent elections in 2019, these elections are not included in the sample. The number of police stations refers to the police stations that were mapped to non-split police stations. Although the state of Jammu & Kashmir was later reorganized into 2 UTs by the central government, I treat it as a single state as this was the case for the entire duration of my study.

Table 3.B.2: Summary of States and UTs Not Included

Type	**State**	**Reason for Exclusion**
State	Bihar	No crime data
State	Meghalaya	Electoral data not matched
State	Orissa	No mapping data
State	Tripura	No crime data
State	West Bengal	No mapping data
UT	Andaman and Nicobar Islands	No crime data
UT	Chandigarh	Union Territory - no assembly elections
UT	Dadra and Nagar Haveli	Union Territory - no assembly elections
UT	Daman and Diu	Union Territory - no assembly elections
UT	Lakshadweep	Union Territory - no assembly elections

Notes: The table lists the five states and five union territories that are not included in the data and the reason for their exclusion.

3.C Mapping and Police Station Types

Police stations can be of three types - *non-split*, where each police station is assigned only to one constituency; *split*, where a police station can be assigned to multiple constituencies; and *special*, where a police station records particular kinds of cases from a larger administrative area which is likely to contain multiple constituencies (for example, women police stations). 60.52% of the police stations are non-split. The distribution of the three kinds of police stations and their share in total crime varies by state. Split police stations are shared between a minimum of two and a maximum of seven assembly constituencies.[78] For the purpose of my analysis, I exclude all police stations that are either *split* or *special*, and use only *non-split* police stations, restricting my sample to 8,034 police stations.

Table 3.C.3: Distribution of Police Station Type

Police Station Type	Frequency	Share
Nonsplit	8,034	60.52
Split	3,748	28.23
Special	1,494	11.25
Total	13,276	100.00

Notes: The table presents the distribution of police station types for the sample of 26 states and union territories in India. Crime, mapping or electoral data is unavailable for 6 states. 4 union territories do not have state-level assembly constituencies, and are not included here.

Table 3.C.4: Summary of Crime Count at the PS-Day Level by Police Station Type

PS Type	Observations	Mean	Std. Dev.	Min.	Max.
Non-Split	10,228,229	4.577614	6.181674	0	1271
Split	4,992,238	4.814127	5.243583	0	686
Special	674,695	4.148317	6.338718	0	796
Unknown	2,195,989	5.042753	9.589398	0	1792

Notes: The table presents the summary statistics of the variable crime count by type of police station. Police stations that are 'unknown' were excluded from the mapping and their assignment to any constituency is unknown. Only non-split police stations are used to produce the empirical results in the paper.

[78] This is most likely to be the case in large urban cities where constituencies cover smaller geographical area and are close together.

3.D Datasets

Table 3.D.5: Datasets Used in the Main Analysis

Dataset	Period	Source
Crime Records	2008-2019	National Crime Records Bureau, Government of India
PS-AC Mapping		State Police Departments
Politicians' Affidavits	2008-2019	myneta.info (ADR, 2021)
Electoral Outcomes	2008-2019	Lok Dhaba data from Trivedi Center of Political Data (Bhogale et al., 2019)
Census	2011	Socioeconomic High-resolution Rural-Urban Geographic Panel for India (Asher et al., 2019)
Political Violence	2016-2019	Armed Conflict Location and Events Data (ACLED) Project (Raleigh et al., 2010)
Domestic Violence Victimization	2015-2016	International Institute for Population Sciences - IIPS/India and ICF, 2017. National Family Health Survey NFHS-4, 2015-16.
Crime Victimization	2011-2012	India Human Development Survey-II (Desai and Vanneman, 2018)

3.D.1 Variables Used from DHS

Experienced Domestic Violence. To calculate the share of women who had ever experienced domestic violence, the denominator or base was all women selected and interviewed as a part of the domestic violence module. Following the DHS Manual and Codebook, the number of women who experienced violence (D106 = 1 or D107 = 1 or D108 = 1 or D130A = 1 or D130B = 1 or D115Y = 0 or D118Y = 0 or D125 = 1) was measured (ICF, 2018). Where: D106 Experienced any less severe violence. D107 Experienced any severe violence. D108 Experienced any sexual violence. D130A Previous husband: ever hit, slap, kick or physically hurt respondent. D130B Previous husband: physically forced to have sex or to perform sexual acts. D115Y No one other than spouse (physical abuse by others than husband). D118Y No one (physical abuse while pregnant). D125 Anyone forced respondent to perform sexual acts. Base: All women eligible for domestic violence and interviewed (V044 = 1).

Sought Help from Police. To calculate the share of all women who sought help from the police to stop the violence, the base was all women who had experience domestic violence. Base: Women who experienced violence (D106 = 1 or D107 = 1 or D108 = 1 or D130A = 1 or D130B = 1 or D115Y = 0 or D118Y = 0 or D125 = 1). D119XE: Sought help from the Police to stop violence.

Both these variables were calculated in the IAIR74DT dataset and then collapsed to the constituency-month level using analytical weights (D005: Weight for domestic violence respondents) given in the dataset.

3.D.2 Data from IHDS2

The IHDS2 survey asks households four questions about local crime (Desai and Vanneman, 2018). The relevant questions of the IHDS2 are as given below.

Now, I would like to ask you some questions about the safety of your village/urban neighbourhood.

- LC1: During the last twelve months, was anything stolen that belonged to you or to somebody in your household? No=0 and Yes=1
- LC2: During the last twelve months, did anyone break into your home or illegally get into your home? No=0 and Yes=1
- LC3: During the last twelve months, did anyone attack or threaten you or someone in your household? No=0 and Yes=1
- LC4: How often are unmarried girls harassed in your village/urban neighbourhood? Rarely / Never=1, Sometimes=2, Often=3.

I re-coded LC4 in the data analysis where the variable took the value 0 if LC4 was 1 (rarely or never), and 1 if LC4 was either 2 or 3 (sometimes or often).

3.E RD with Candidate Characteristics that are Discontinuous at Cut-off

As per Table 3.4, covariates measuring candidates' education and party membership are not smooth at the cut-off. In this section, I re-run the main RD regressions using these covariates as the running variables, and I find no impact of candidates' education or party membership on all the five main measures of local crime. Table 3.E.6 displays the results using literacy status of candidate as the assignment variable. Table 3.E.7 uses the graduate or graduate professional status of the candidate. Table 3.E.8 presents the results using the party membership of the candidate as assignment variable.

Table 3.E.6: Impact of Literate Politician on Weekly Crime Outcomes

	(1) Cases	(2) Violations	(3) Crime	(4) Non-Penal Code	(5) Serious
RD Estimate	-0.167	-0.0783	-0.0931	0.00773	-0.247
Robust Std. Error	.558	.661	.568	.314	.354
Robust p-value	.514	.529	.519	.624	.311
Observations	107242	107242	107242	107242	98666

Notes: The table presents regression discontinuity estimates of the impact of having an illiterate (or education not given) politician versus a literate politician in office on various crime outcomes. All estimates are derived from a sharp RD design with triangular kernel-weighted local linear estimates over a fixed bandwidth of 0.085. Conventional RD point estimates are presented along with robust RD standard errors and p-values. Column 1 presents results for the total number of FIRs registered. Column 2 presents results for the total number of crime violations. Columns 3 and 4 present results for the count of IPC and non-IPC violations, respectively. Column 5 presents results for serious IPC crimes. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the constituency-assembly period level. Week, year, and police station fixed effects are included. No other covariates are included.

Table 3.E.7: Impact of Graduate/Professional Politician on Weekly Crime Outcomes

	(1) Cases	(2) Violations	(3) Crime	(4) Non-Penal Code	(5) Serious
RD Estimate	-0.0363	-0.0647	-0.103	-0.0295	-0.0750
Robust Std. Error	.144	.175	.159	.121	.118
Robust p-value	.745	.71	.653	.313	.591
Observations	1507389	1507389	1507389	1507389	1479133

Notes: The table presents regression discontinuity estimates of the impact of having a politician with a graduate, post-graduate, graduate professional, or doctorate degree versus politician with lesser education in office on various crime outcomes. All estimates are derived from a sharp RD design with triangular kernel-weighted local linear estimates over a fixed bandwidth of 0.085. Conventional RD point estimates are presented along with robust RD standard errors and p-values. Column 1 presents results for the total number of FIRs registered. Column 2 presents results for the total number of crime violations. Columns 3 and 4 present results for the count of IPC and non-IPC violations, respectively. Column 5 presents results for serious IPC crimes. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the constituency-assembly period level. Week, year, and police station fixed effects are included. No other covariates are included.

Table 3.E.8: Impact of Regional Party Politician on Weekly Crime Outcomes

	(1) Cases	(2) Violations	(3) Crime	(4) Non-Penal Code	(5) Serious
RD Estimate	0.00884	-0.0208	-0.0475	0.0512	-0.0306
Robust Std. Error	.127	.172	.151	.118	.114
Robust p-value	.325	.414	.291	.941	.609
Observations	1486032	1486032	1486032	1486032	1462156

Notes: The table presents regression discontinuity estimates of the impact of party membership (having a politician belonging to a party other than the BJP or INC) on various crime outcomes. All estimates are derived from a sharp RD design with triangular kernel-weighted local linear estimates over a fixed bandwidth of 0.085. Conventional RD point estimates are presented along with robust RD standard errors and p-values. Column 1 presents results for the total number of FIRs registered. Column 2 presents results for the total number of crime violations. Columns 3 and 4 present results for the count of IPC and non-IPC violations, respectively. Column 5 presents results for serious IPC crimes. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the constituency-assembly period level. Week, year, and police station fixed effects are included. No other covariates are included.

3.F Results using Optimal rather than Fixed Bandwidth

The results in the main paper use a fixed bandwidth of 8.5% to maintain consistency in the sample. This section presents all the main results from the paper using the optimal rather than the fixed bandwidth. I show that the results remain robust to the use of the optimal bandwidth. The mean squared error optimal bandwidth for each regression is calculated following Calonico, Cattaneo and Titiunik (2014).

3.F.1 Results from Section 3.4 using Optimal Bandwidth

Table 3.F.9: Impact of Criminal Politician on Weekly Crime Outcomes over Optimal Bandwidth

	(1) Case	(2) Violation	(3) Crime	(4) Non-Penal Code
Criminal	-0.0941	-0.221	-0.230	-0.0491
Robust Std. Error	.114	.144	.139	.079
Robust p-value	.297	.068	.051	.41
Mean	1.688	2.239	1.912	1.084
Effect Size (%)	-5.57	-9.87	-12.02	-4.53
Bandwidth	.098	.092	.091	.122
Observations	1251985	1251985	1251985	1251985
Bandwidth obs.	693055	668128	662191	812692

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on various crime outcomes. All estimates are derived from a sharp RD design with triangular kernel-weighted local linear estimates over the optimal bandwidth calculated using the Stata command 'rdrobust'. The mean squared error optimal bandwidth is calculated following Calonico, Cattaneo and Titiunik (2014). Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. Column 1 presents results for the total number of FIRs registered. Column 2 presents results for the total number of crime violations. Columns 3 and 4 present results for the count of IPC and non-IPC violations, respectively. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the constituency-assembly period level. Week, year, and police station fixed effects are included. No other covariates are included.

Table 3.F.10: Regression Discontinuity Estimates by IPC Chapter over Optimal Bandwidth

Chp.	Description	RD Estimate	Robust p-value	Bandwidth
1	Introduction	0.0004	.529	.12
2	General Explanations	-0.1217	.012	.083
3	Of Punishments	-0.0005	.165	.086
4	General Exceptions	-0.0000	.91	.105
5	Of Abetment	0.0132	.291	.125
6	Of Offences against the State	0.0002	.345	.087
7	Of Offences relating to the Army, Navy and Air Force	-0.0004	.427	.077
8	Of Offences against the Public Tranquillity	-0.0241	.319	.103
9	Of Offences by or relating to Public Servants	-0.0017	.196	.114
10	Of Contempts of Lawful Authority of Public Servants	0.0133	.254	.11
11	Of False Evidence and Offences against Public Justice	-0.0069	.004	.068
12	Of Offences relating to coin and Government Stamps	-0.0001	.88	.083
13	Of Offences relating to Weight and Measures	-0.0000	.941	.122
14	Of Offences affecting the Public Health, Safety, Convenience, Decency and Morals	-0.0275	.584	.141
15	Of Offences relating to Religion	-0.0020	.03	.11
16	Of Offences affecting the Human Body	-0.1778	.028	.095
17	Of Offences Against Property	-0.1533	.03	.086
18	Offences relating to Documents and Property Marks	-0.0177	.069	.096
19	Of the Criminal Breach of Contracts of Service	-0.0000	.62	.117
20	Of Offences Relating to Marriage	-0.0014	.438	.089
21	Of Defamation	-0.0011	.034	.1
22	Of Criminal intimidation, Insult and Annoyance	-0.1051	.066	.105
23	Of Attempts to Commit Offences	-0.0063	.058	.106
5A	Criminal Conspiracy	-0.0086	.232	.116
9A	Of Offences Relating to Elections	-0.0002	.732	.112
20A	Of Cruelty by Husband or Relatives of Husband	-0.0136	.254	.112

Notes: The table presents RD estimates of the impact of having a criminal politician in office on the weekly IPC count by chapter. All estimates are derived from a sharp RD design with triangular kernel-weighted local linear estimates using the Stata command 'rdrobust' over the optimal bandwidth. The mean squared error optimal bandwidth for each regression is calculated following Calonico, Cattaneo and Titiunik (2014). Conventional RD estimates and robust RD p-values are presented. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the constituency-assembly period level. Week, year, and police station fixed effects are included. No other covariates are included. The total number of observations in each regression is 1251985. The number of observations within the optimal bandwidth for each regression varies and is not shown here.

3.F.2 Results from Section 3.5 using Optimal Bandwidth

Table 3.F.11: Impact of Criminal Politician on Weekly Count of Murder over Optimal Bandwidth

	(1) Murder
Criminal	-0.00436
Robust Std. Error	.004
Robust p-value	.2
Mean	.029
Effect Size (%)	-15.25
Bandwidth	.106
Observations	1241248
Bandwidth obs.	732095

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly murder count. The dependent variable is transformed using the inverse hyperbolic sine transformation. Week, year and police station fixed effects are included. The RD is conducted at the mean squared error optimal bandwidth following Calonico, Cattaneo and Titiunik (2014). Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

3.F.3 Results from Section 3.6 using Optimal Bandwidth

Using the optimal rather than the fixed bandwidth in the RD with criminal types, I find that there is no longer any significant decrease in areas with a serious criminal politician, as compared to areas with a non-criminal politician. The decline in the case of the comparison of non-serious criminal politicians and non-criminal politicians remains negative and significant (Table 3.F.14). On the other hand, there are significantly lower murders in serious criminal areas compared to non-criminal areas, and no significant difference in murders in non-serious criminal areas compared to non-criminal areas (Table 3.F.15).

Table 3.F.12: Impact on Political Violence over Optimal Bandwidth

	(1) ACLED Count	(2) ACLED Fatalities	(3) NCRB Count	(4) IPC Serious
Criminal	-0.008	-0.001	-0.049	-0.184
Robust Std. Error	.017	.001	.032	.124
Robust p-value	.462	.141	.114	.106
Bandwidth	.0615885	.0590758	.1276146	.1178522
Observations	171203	171203	525829	522979
Bandwidth obs.	59404	57347	336779	318727
Unit FE	Constituency	Constituency	Police Station	Police Station
Year FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly levels of political violence, defined as protests, riots and violence against civilians. The dependent variables are transformed using the inverse hyperbolic sine transformation. Columns 1 and 2 presents results from a RD regression at the assembly constituency level with week, year and constituency fixed effects using the State 'rdrobust' command. Columns 3 and 4 present results from a RD regression at the police station level with week, year and police station fixed effects for the period 2016-2019. Conventional RD point estimates are presented along with robust RD standard errors and p-values. The dependent variables in columns 3 and 4 are IPC Chapter 8 (offences against public tranquillity) and serious IPC crimes. The period under consideration is 2016-2019, for which the ACLED data is available. All the regressions are conducted at the mean squared error optimal bandwidth following Calonico, Cattaneo and Titiunik (2014). Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

Table 3.F.13: Impact of Criminal Politicians on Weekly Domestic Violence over Optimal Bandwidth

	(1) Full Sample	(2) 2015m1-2016m12	(3) 2008m3- 2016m12
Criminal	-0.014	-0.016	-0.017
Robust Std. Error	.014	.017	.017
Robust p-value	.254	.326	.191
Bandwidth	.112	.102	.096
Observations	1241248	282903	860734
Bandwidth obs.	760819	159469	484235

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly levels of domestic violence, defined as Section 498A of the IPC. The dependent variable is transformed using the inverse hyperbolic sine transformation. The period under consideration varies for the three columns. All the regressions are conducted at the mean squared error optimal bandwidth following Calonico, Cattaneo and Titiunik (2014). Conventional RD point estimates are presented along with robust RD standard errors and p-values. Standard errors are clustered at the constituency-assembly period level. Week, year and police station fixed effects are included. No other covariates are included.

Table 3.F.14: Impact of Criminal Politician by Type on Weekly Serious Crime over Optimal Bandwidth

	(1) SCP vs NCP	(2) NSCP vs NCP
Criminal	-0.118	-0.416
Robust Std. Error	.13	.171
Robust p-value	.308	.006
Mean	1.266	1.318
Effect Size (%)	-9.29	-31.56
Bandwidth	.106	.086
Observations	790462	346170
Bandwidth obs.	472039	173272

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly serious IPC count. Column 1 compares serious criminal politicians (SCP) with non-criminal politicians (NCP), and Column 2 compares 'non-serious' criminal politicians (NSCP) with non-criminal politicians (NCP). The dependent variable is transformed using the inverse hyperbolic sine transformation. Week, year and police station fixed effects are included. The RD is conducted at the mean squared error optimal bandwidth following Calonico, Cattaneo and Titiunik (2014). Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

Table 3.F.15: Impact of Criminal Politician by Type on Weekly Murder over Optimal Bandwidth

	(1) SCP vs NCP	(2) NSCP vs NCP
Criminal	-0.00795	0.00211
Robust Std. Error	.005	.006
Robust p-value	.072	.588
Mean	.031	.028
Effect Size (%)	-25.79	7.65
Bandwidth	.109	.11
Observations	788979	345691
Bandwidth obs.	476086	213651
Police Station FE	Yes	Yes
Year FE	Yes	Yes
Week FE	Yes	Yes

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly murder count. Column 1 compares serious criminal politicians (SCP) with non-criminal politicians (NCP), and Column 2 compares 'non-serious' criminal politicians (NSCP) with non-criminal politicians (NCP). The dependent variable is transformed using the inverse hyperbolic sine transformation. Week, year and police station fixed effects are included. The RD is conducted at the mean squared error optimal bandwidth following Calonico, Cattaneo and Titiunik (2014). Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

3.G Robustness Tests

3.G.1 Alternative RD Specifications

I test whether the RD estimates remain robust to using a local quadratic polynomial estimation, and to the use of alternative kernel functions and bandwidths. I also undertake a placebo test to show that the results do not hold at alternative cut-off points in the running variable. I have previously shown in Table 3.5 that results remain robust to the inclusion and exclusion of fixed effects. Table 3.G.16 presents the main results using a local quadratic estimation, and shows that the results remain consistent. All tables present conventional RD estimates with robust RD standard errors and p-values.

3.G.1.1 Alternative Kernel Functions

In the main analysis, I use triangular kernel functions, which give a higher weight to observations closer to the cut-off. I undertake robustness checks that use alternative kernel functions - the epanechnikov and the uniform kernel functions. The main results remain robust to the use of alternative kernel functions.

3.G.1.2 Alternative Clustering

The main analysis uses standard errors that are clustered at the level of the assembly constituency-assembly period. In Table 3.G.18, I present the results using standard errors that are clustered at the constituency (Columns 1 and 2) and police station (Column 3 and 4) levels, respectively. The results remain consistent to the use of alternative forms of clustering.

3.G.1.3 Alternative Bandwidths

The results presented so far use the optimal bandwidth of 8.5% margin of victory. I

Table 3.G.16: Impact of Criminal Politician on Weekly Serious Crime using Alternative Specifications

	(1)	(2)	(3)	(4)
Criminal	-0.249	-0.265	-0.219	-0.239
Robust Std. Error	.114	.114	.11	.112
Robust p-value	.02	.013	.034	.021
Mean	1.279	1.278	1.28	1.278
Effect Size (%)	-19.5	-20.76	-17.14	-18.73
Bandwidth	.179	.166	.183	.167
Observations	1243461	1243461	1243461	1243461
Bandwidth obs.	991279	951910	1002336	953723
Police Station FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
Week FE	No	Yes	No	Yes

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on the weekly serious IPC count. All estimates are derived from a sharp RD design with triangular kernel-weighted local quadratic estimates over the optimal bandwidth calculated using the Stata command 'rdrobust'. Conventional RD point estimates are presented along with robust RD standard errors and p-values. The mean is calculated for the outcome variable in the control group of the estimation sample, i.e., where the assignment variable takes the value zero. The mean squared error optimal bandwidth is calculated following Calonico, Cattaneo and Titiunik (2014). Column 1 presents the RD estimates without inclusion of any other covariates or fixed effects. Column 2 includes time fixed effects. Column 3 includes police station fixed effects. Column 4 presents results including week, year, and police station fixed effects. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the constituency-assembly period level. No other covariates are included.

Table 3.G.17: Impact of Criminal Politician on Weekly Serious Crime using Alternative Kernel Functions

	(1) Epanechnikov	(2) Epanechnikov	(3) Uniform	(4) Uniform
Criminal	-0.223	-0.364	-0.150	-0.392
Robust Std. Error	.136	.182	.131	.175
Robust p-value	.007	.109	.003	.096
Police Station FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Polynomial	Linear	Quadratic	Linear	Quadratic
Bandwidth	0.085	0.085	0.085	0.085
Observations	1243461	1243461	1243461	1243461
Bandwidth obs.	628591	628591	628591	628591

Notes: The table presents estimates from a RD regression of the impact of having a criminal politician in office on the weekly serious IPC count at the police station level using the 'rdrobust' command in Stata. Sharp RD estimates are reported. The mean squared error optimal bandwidth is calculated following Calonico, Cattaneo and Titiunik (2014). Columns 1 and 2 present epanechnikov kernel-weighted estimates, and Columns 3 and 4 present uniform kernel-weighted estimates. A local linear regression is used in Columns 1 and 3. A local quadratic regression is used in Columns 2 and 4. Conventional RD point estimates are presented along with robust RD standard errors and p-values. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the assembly constituency-assembly period level. Police station, year, and week fixed effects are included. No other covariates are included.

Table 3.G.18: Impact of Criminal Politician on Weekly Serious Crime using Alternative Clustering

	(1) AC Cluster	(2) AC Cluster	(3) PS Cluster	(4) PS Cluster
Criminal	-0.267	-0.237	-0.267	-0.237
Robust Std. Error	.147	.138	.093	.092
Robust p-value	.009	.012	0.000	0.000
Police Station FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Week FE	No	Yes	No	Yes
Bandwidth	0.085	0.085	0.085	0.085
Observations	1243461	1243461	1243461	1243461
Bandwidth obs.	628591	628591	628591	628591

Notes: The table presents estimates from a RD regression of the impact of having a criminal politician in office on the weekly serious IPC count at the police station level using the 'rdrobust' command in Stata. Sharp RD, triangular kernel-weighted local linear estimates in the optimal bandwidth are reported. The mean squared error optimal bandwidth is calculated using the Stata command 'rdrobust' following Calonico, Cattaneo and Titiunik (2014). Standard errors in columns 1 and 2 are clustered at the level of the assembly constituency, and in columns 3 and 4 are clustered at the level of the police station. Police station, year, and week fixed effects are included in Columns 2 and 4. Conventional RD point estimates are presented along with robust RD standard errors and p-values. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. No other covariates are included.

test the main result at alternative margins, and find that the results remain robust.

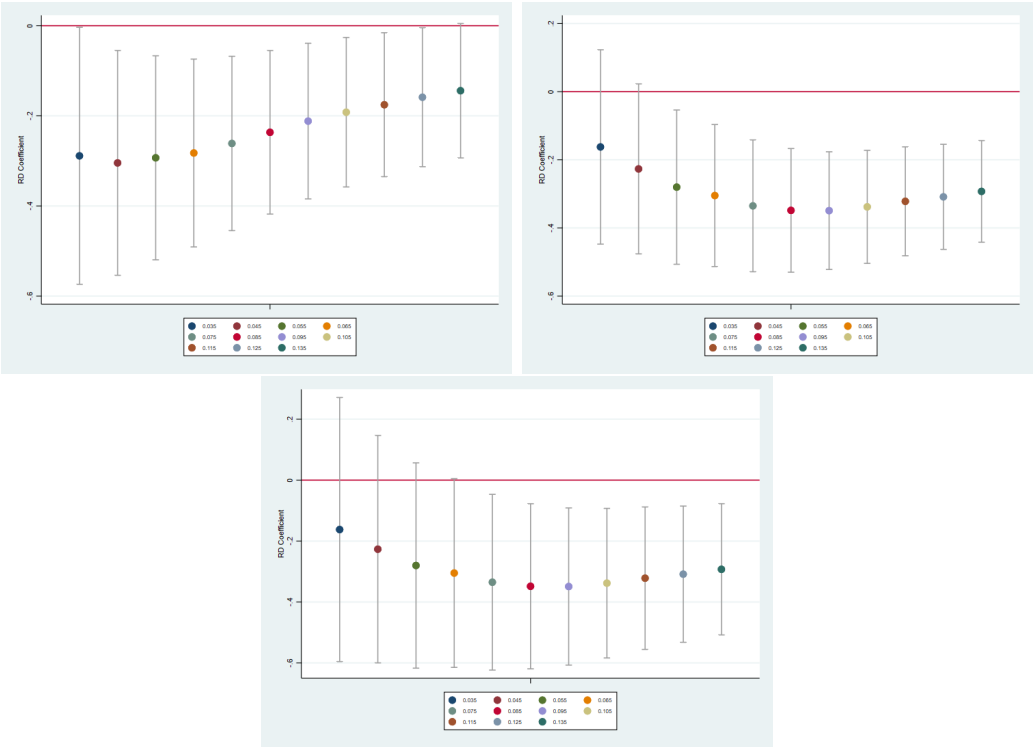
3.G.1.4 Placebo Tests: Using different cut-off points

I conduct placebo tests for the RD design, using cut-offs other than that of a margin of zero. The results for the zero cut-off are shown for comparison.

3.G.2 Coverage

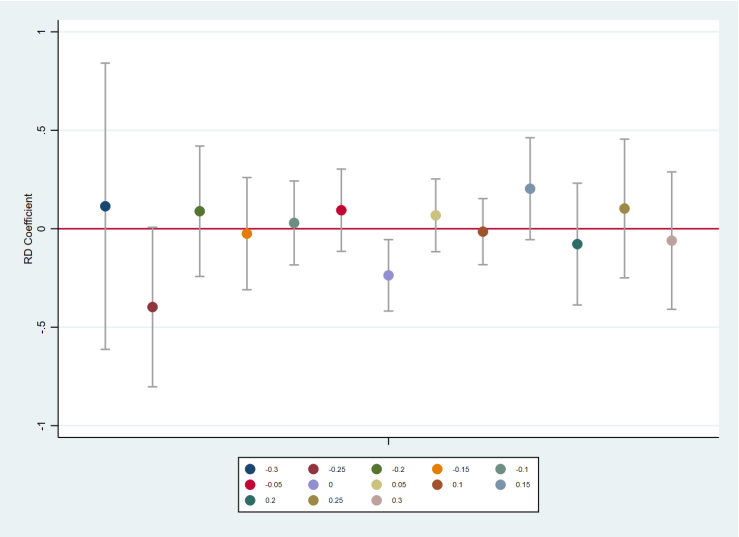
In this sub-section, I show that results are robust to the exclusion of various states, including those with poor data availability. I drop states for which data is available for less than 60% of the constituencies within the state. This includes the six states/UTs of Goa, Mizoram, Nagaland, Puducherry, Rajasthan and Sikkim, which account for 6.18% of the population (Census of India, 2011). The results, shown in

Figure 3.G.3: Results are Robust at Alternative RD Bandwidths



Notes: The figure presents a coefficient plot of the regression discontinuity estimates of the impact of having a criminal politician in office on serious IPC crime at the weekly level using different bandwidths between 3.5% and 13.5% to ensure that the results are not driven by the bandwidth. The dependent variable is transformed using the inverse hyperbolic sine transformation. For comparison, the main estimates use the mean squared error optimal bandwidth of 8.5% following Calonico, Cattaneo and Titiunik (2014). Panel A uses conventional RD estimates, panel B uses bias-corrected estimates, and panel C uses robust RD estimates. Standard errors are clustered at the assembly constituency-assembly period level. Police station, year, and week fixed effects are included. No other covariates are included.

Figure 3.G.4: Placebo Tests with Alternative Cut-off Points

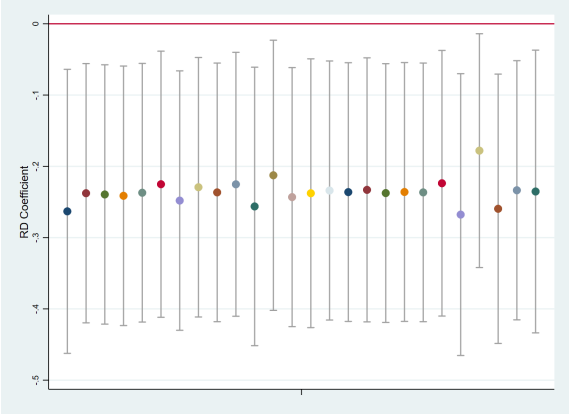


Notes: This figure presents the coefficients from a simple RD regression using the 'rdrobust' command in Stata. Sharp, conventional RD estimates using a local linear regression are presented. An optimal bandwidth of 0.085 is used. Standard errors are clustered at the assembly constituency-assembly period level. Estimates are adjusted for mass points in the running variable. Week, year, and police station fixed effects are included.

Table 3.G.19, remain significant after dropping these states.

Figure 3.G.5 shows the results of the analysis, dropping one state at a time. The coefficient of *Criminal* for each regression, excluding the labelled state, is presented in the coefficient plot. Results are robust to the exclusion of individual states.

Figure 3.G.5: Results Remain Robust to Exclusion of Individual States



Notes: The figure presents the conventional estimates from the main RD regressions after excluding one state/UT at a time. The y-axis presents the coefficient of the variable *Criminal*, after excluding the labelled state from the analysis. Week, year, and police station fixed effects are included. Results are calculated using a triangular kernel in a local linear regression over the optimal bandwidth of 0.085.

I also ensure that the results are robust to the exclusion of outliers. I trim the crime

Table 3.G.19: Results Remain Robust after Excluding States with Low Data Availability

	(1)
Criminal	-0.234
Robust Std. Error	.139
Robust p-value	.012
Bandwidth	0.085
Observations	1235528
Bandwidth obs.	626612

Notes: The table presents estimates from a RD regression of the impact of having a criminal politician in office on the weekly serious IPC count at the police station level using the 'rdrobust' command in Stata. The states of Goa, Mizoram, Nagaland, Puducherry, Rajasthan and Sikkim are excluded from the analysis. Sharp RD, triangular kernel-weighted estimates from a local linear regression in the optimal bandwidth of 0.085 are reported. The mean squared error optimal bandwidth is calculated using the Stata command 'rdrobust' following Calonico, Cattaneo and Titiunik (2014). Conventional RD point estimates are presented along with robust RD standard errors and p-values. Estimates are adjusted for mass points in the running variable. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the assembly constituency-assembly period level. Police station, year, and week fixed effects are included. No other covariates are included.

data to exclude values that are below the 1^{st} and above the 99^{th} percentiles of the distribution of weekly Serious IPC Count. I winsorize the data by re-coding the values below the 1^{st} and above the 99^{th} percentiles of the distribution to the value of the 1^{st} and 99^{th} percentiles, respectively. I do the same for the 5^{th} and the 95^{th} percentiles as well. Table 3.G.20 presents the results for the analysis using trimmed and winsorized data.

3.G.3 Timing

This subsection looks at the role of timing, and shows that the results are robust to two important considerations - the inclusion of the election period, and the proximity to the election. Results are not driven by the month immediately preceding or succeeding an election period.

The analysis so far does not include the election period, defined as the duration between the election schedule being announced and the election results being declared.

Table 3.G.20: Impact of Criminal Politician on Weekly Serious Crime Excluding Outliers

	(1) Trimmed 1-99	(2) Winsorized 1-99	(3) Trimmed 5-95	(4) Winsorized 5-95
Criminal	-0.215	-0.236	-0.188	-0.231
Robust Std. Error	.135	.138	.129	.136
Robust p-value	.012	.009	.015	.009
Bandwidth	0.085	0.085	0.085	0.085
Observations	1232175	1251985	1212268	1251985
Bandwidth obs.	623606	630479	614581	630479

Notes: The table presents estimates from a RD regression of the impact of having a criminal politician in office on the weekly serious IPC count at the police station level using the 'rdrobust' command in Stata. The dependent variable, serious IPC count, is trimmed or winsorized, and then transformed using the inverse hyperbolic sine transformation. Columns 1 and 3 trim the data to exclude the top and bottom 1% and 5% of observations, respectively. Columns 2 and 4 replace the top and bottom 1% and 5% of values with the value at the 1st/99th, and 5th/95th percentiles, respectively. Sharp RD, triangular kernel-weighted estimates from a local linear regression in the optimal bandwidth of 0.085 are reported. The mean squared error optimal bandwidth is calculated using the Stata command 'rdrobust' following Calonico, Cattaneo and Titiunik (2014). Conventional RD point estimates are presented along with robust RD standard errors and p-values. Estimates are adjusted for mass points in the running variable. Standard errors are clustered at the assembly constituency-assembly period level. Police station, year, and week fixed effects are included. No other covariates are included.

This period lasts for a median duration of 9 weeks across different states and years. Election periods may have different dynamics compared to non-election periods, as discussed in Chapter 2 of this thesis. I test whether the results are being driven by the exclusion of election periods. I include two additional variables in the main RD specification. *Election* takes the value 1 in an election week and 0 in a non-election week. $Election * Criminal$ is the interaction of *Election* indicator with the treatment variable, *Criminal*. In the full sample, 2.35 percent of all observations are in the election period and the remaining 97.65 percent are in non-election periods.

$$Crime_{ij} = \beta_0 + \beta_1 Criminal_j + \beta_2 Margin_j + \beta_3 Criminal_j * Margin_j + \beta_4 Election_j + \beta_5 Criminal_j * Election_j + \alpha_{ij} + \gamma_{ij} + \epsilon_{ij}$$

I attribute the crime committed during the electoral period to the government that is in power in the preceding period. For example, the crime committed in the transition between period 1 and period 2 is attributed to politician in power in period 1.

Column 1 of Table 3.G.21 presents the main results using the fixed effects estimation.[79] This shows that the coefficient of *Criminal* is negative and significant, as in the main results. Column 2 of Table 3.G.21 presents the results from the fixed effects estimation, including the election period, and shows that crime continues to be lower in criminal areas, even including the election period. I further consider the 4 week period right after the results of the election are declared, and the 4 week period right before elections are announced to test whether the decrease in crime is being driven by periods immediately after or immediately before an election. As can be seen from Column 3, this is not the case. While crime is lower in the month before and after an election, the coefficient of *Criminal* remains negative and significant.

Finally, I also run the RD regression over restricted six-month sub-samples for the duration of the entire 5-year electoral period. The conventional RD estimates for each period are plotted in Figure 3.G.6 and support the idea that there is no significant heterogeneity over time during the period that criminal politicians are in office. During the last three six-month sub-periods, the effects begins to wane and there is no significant difference in crime in criminal and non-criminal areas.

[79] The Stata command 'rdrobust' can no longer be used in this case as we are interested in other coefficients in addition to the RD coefficient.

Table 3.G.21: Results are not driven by Timing

Serious Crime Count	(1)	(2)	(3)
Criminal	-0.174**	-0.175**	-0.179**
	(0.070)	(0.070)	(0.071)
Margin	0.0660	0.0701	0.0473
	(0.934)	(0.934)	(0.962)
Criminal*Margin	3.488***	3.490***	3.582***
	(1.311)	(1.310)	(1.331)
Election		0.000558	
		(0.028)	
Criminal*Election		0.0142	
		(0.036)	
Month after Election			-0.0818***
			(0.018)
Month before subsequent Election			-0.164***
			(0.029)
Criminal*Month after Election			-0.0156
			(0.024)
Criminal*Month before subsequent Election			0.0636
			(0.040)
Constant	1.278***	1.278***	1.278***
	(0.043)	(0.043)	(0.044)
Police Station FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Bandwidth	0.085	0.085	0.085
Observations	644341	644341	628591

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on serious IPC crime at the weekly level to ensure that the results are not driven by timing. The dependent variable is transformed using the inverse hyperbolic sine transformation. The estimates are produced using using a fixed effects regression at the police station level, with time fixed-effects using the Stata command 'reghdfe'. Mixed races within the optimal bandwidth are included. Standard errors are clustered at the assembly constituency-assembly period level. No other covariates are included.

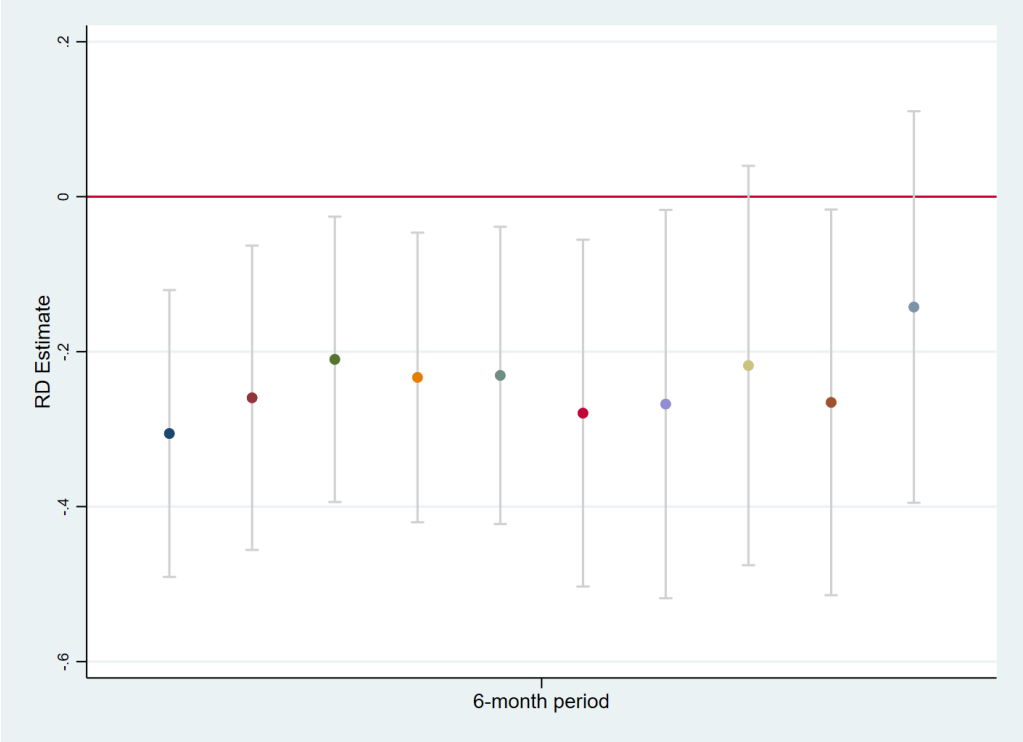


Figure 3.G.6: Time Heterogeneity of RD Coefficient

Notes: The figure presents a coefficient plot of the conventional regression discontinuity estimates of the impact of having a criminal politician in office on serious crime for six-month intervals over the five-year election period. The dependent variable is transformed using the inverse hyperbolic sine transformation. Standard errors are clustered at the assembly constituency-assembly period level. Police station, year, and week fixed effects are included. No other covariates are included.

3.H Tests of RD Validity for Heterogeneity

This section tests the validity of the RD identifying assumptions (continuity of covariates at the cut-off, and no sorting) for the regression discontinuity models that look at the impact of serious and non-serious criminal politicians separately.

Table 3.H.22: Smoothness of Constituency Characteristics at Cut-off by Politician Type

	SCP vs NCP			NSCP vs NCP		
Variable	Difference	p	N	Difference	p	N
Per capita consumption (Rs.)	-240.943	0.735	412	-618.121	0.655	155
Agricultural households (%)	-0.039	0.223	414	-0.06	0.186	159
Pre-period Serious IPC Count	-0.168	0.680	414	-0.52	0.413	254
Literacy Rate	0.016	0.388	625	0.014	0.706	162
Share of Population Urban	0.052	0.167	423	0.093	0.238	162
SC/ST Share	-0.007	0.841	423	-0.045	0.327	162
Number of households	3796.522	0.312	423	3785.693	0.405	162
Total non-farm employment (2013)	2809.686	0.429	423	-1873.812	0.65	154
Total non-farm employment (2005)	2266.366	0.377	412	93.572	0.979	135
Average Nightlights (2008)	5.261	0.068	381	-0.312	0.94	237
Average Forest Cover (2008)	-1.348	0.377	593	4.768	0.041	237
Area of town (sq.km.)	11.157	0.065	593	-10.248	0.342	145
Number of senior secondary schools (T)	-1.975	0.380	368	1.31	0.512	145
Number of colleges (T)	1.438	0.222	368	1.801	0.344	145
Number of secondary schools (T)	-1.024	0.768	368	4.339	0.244	145
Number of middle schools (T)	2.52	0.792	368	4.228	0.513	145
Number of primary schools (T)	7.122	0.494	368	6.456	0.484	145
Power supply for all users (%)	-0.049	0.420	368	-0.097	0.18	160
Area of village (hectares)	-1919.475	0.874	422	1683.653	0.941	160
Accessibility by paved road	-0.001	0.983	422	-0.043	0.407	160
Number of colleges (V)	-0.586	0.497	422	0.083	0.948	160
Number of senior secondary schools (V)	0.282	0.903	422	-3.336	0.328	160
Number of secondary schools (V)	-1.24	0.780	422	-4.03	0.558	160
Number of middle schools (V)	-1.207	0.926	421	0.327	0.988	160
Number of primary schools (V)	2.948	0.907	422	27.268	0.523	160

Notes: The table presents balance between treated and untreated units using the OLS specification at the optimal bandwidth. Difference represents the treatment effect of having a criminal politician on each of the outcome variables. Margin and the interaction of Criminal and Margin are included as controls. Standard errors are clustered at the constituency-assembly period level. (T) and (V) refer to town and village-level measures, respectively. All outcome variables are at the constituency level, except for turnout and incumbent, which are at the constituency-assembly period level. Agricultural households refers to households with main income from cultivation.

Table 3.H.23: Smoothness of Candidate Characteristics at Cut-off by Politician Type

	SCP vs NCP			NSCP vs NCP		
Variable	Difference	p	N	Difference	p	N
Male (1/0)	-0.034	0.203	1,276	-0.017	0.650	512
Illiterate (1/0)	0.006	0.287	1,276	-0.008	0.320	512
Primary Education (1/0)	0.001	0.946	1,276	0.028	0.112	512
Secondary Education (1/0)	0.005	0.919	1,276	0.039	0.635	512
College (1/0)	-0.055	0.244	1,276	-0.093	0.192	512
Graduate, Graduate Professional or Doctorate (1/0)	0.028	0.582	1,276	0.005	0.948	512
Party = BJP	-0.101	0.007	1,276	-0.102	0.082	512
Party = INC	-0.059	0.114	1,276	0.023	0.683	512
Party other than BJP/INC	0.161	0.004	1,276	0.08	0.372	512
Age	3.896	0.106	286	-2.552	0.480	130
Total Assets (Rs. million)	6.435	0.696	1,276	-4.422	0.808	512
Total Liabilities (Rs. million)	5.326	0.409	1,276	1.586	0.615	512
Effective Number of Parties	0.095	0.532	1,276	0.048	0.805	512
Number of Criminal Cases	0.466	0.267	1,276	-0.005	0.968	512
Total IPC Violations	1.926	0.333	1,274	0.119	0.772	512
Total Serious IPC Violations	0.324	0.42	1,274	0.000	(.)	512

Notes: The table presents balance between treated and untreated units using the OLS specification at the optimal bandwidth of 0.085. Difference represents the treatment effect of having a criminal politician on each of the outcome variables. Margin and the interaction of Criminal and Margin are included as controls. Primary education refers to at most passing the 5th standard. Secondary education refers to at most passing the 8th, 10th, or 12th standards. College refers to at most going to college. Standard errors are clustered at the constituency-assembly period level.

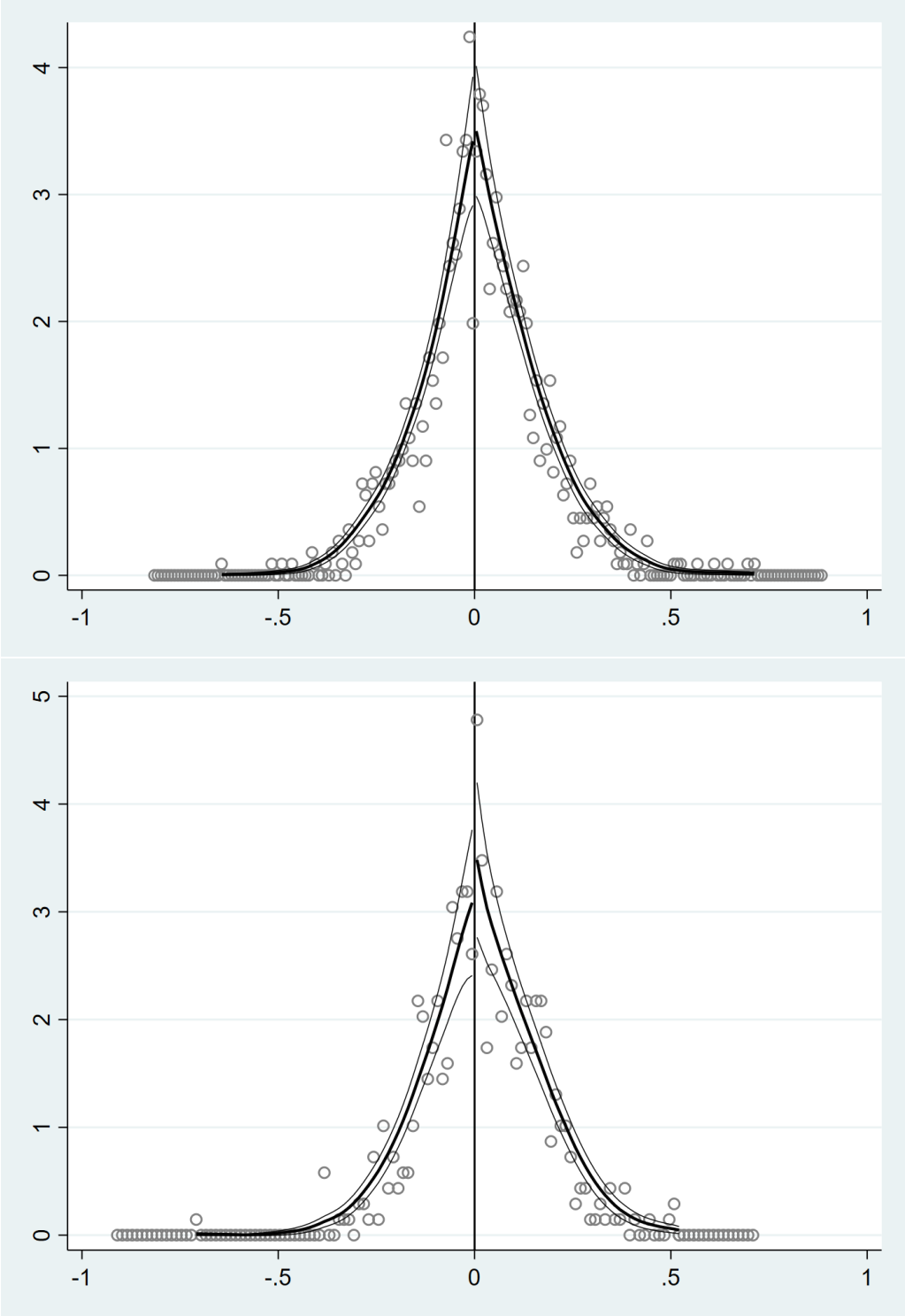


Figure 3.H.7: McCrary Test for Sorting with Alternative Criminality Definitions by Politician Type

Notes: The figure presents the results from the McCrary Test to check if there is manipulation of the running variable. Panel A compares serious criminal politicians with non-criminal politicians. Panel B compares non-serious criminal politicians with non-criminal politicians. I use a constituency-assembly period dataset rather than the full panel dataset. The discontinuity estimate (log difference in height) is 0.019810844 with a standard error of 0.111558292 in Panel A. The discontinuity estimate (log difference in height) in Panel B is 0.127398772 and the standard error is 0.162873839.

3.I Alternative Mechanisms

I test alternative mechanisms looking at the role of *networks*, *authority* and *information*.

Criminal politicians might have had more interactions with the law and order machinery, as compared to non-criminal politicians, and this might be associated with any effectiveness in reducing crime. For example, politicians who have been charged with a greater number of cases, or have been in the system for longer, or have been in office for a greater number of terms, might be better able to control the police, compared to those with less information about how the system works. To test the role of authority, I compare the impact of criminal parliamentarians on crime, relative to the impact of criminal state legislators, as the latter have direct control over the functioning of the police. To test the role of networks, I test whether the impact is different for places where the state has a criminal Chief Minister in the state from the same party as the state legislator.

3.I.1 Networks: Connections with CM

In order to test the role of connections, I obtain information on the Chief Ministers in various states, and the duration for which they were head of government. There is often more than one Chief Ministers during an assembly period as Chief Ministers might govern for temporary periods. There were a total of 109 Chief Ministers over this period for the states under consideration. Of the 91 CMs for whom I was able to match criminal records, 34 were criminally accused (37.36 percent). 35% of Chief Ministers in states have declared criminal cases against themselves (ADR, 2018). Since a Chief Minister (CM) is the head of the government in the state, with de facto executive authority, having a CM who is criminally accused could affect local crime.

I am interested in whether having a criminal CM in the state, who also belongs to the same party as the criminal politician, has any impact on local crime. Variable $CMCriminal$ takes the value 1 if the Chief Minister in the state is also criminally accused, and 0 otherwise. $PartyMatch$ takes the value 1 if the politician under consideration and the Chief Minister belong to the same party, and 0 otherwise. I find that having both a criminal CM and a criminal MLA has a positive impact on local crime. The magnitude of this impact doubles when the criminal MLA and criminal CM belong to the same political party.[80]

3.I.2 Authority: MPs vs MLAs

I hypothesize that since crime and policing are state-level functions, it is the criminality status of the state-level politicians (MLAs) that matters more for outcomes, as compared to the criminality status of national-level politicians (MPs). To verify this, I use an existing dataset on the criminality status of MPs, and then match state assembly and national assembly seats.[81] The variable *MP Criminal* takes the value 1 if the Member of Parliament is also criminally accused, and 0 otherwise. The interaction term *MLA Criminal*MP Criminal* takes the value 1 if both the local MP and MLA are criminally accused, and is 0 otherwise. From Table 3.I.25, we can see that having a criminal at the national level does not make any difference to local crime, whereas the treatment variable *Criminal* (for the MLA) remains negative and significant.

Information. The number of criminal cases does not matter as well. This analysis is the only place in this paper I use the number of cases against a politician rather than a categorization of criminal or non-criminal. I obtain my data by scraping information from the Association of Democratic Reforms website rather than from

[80] When I do this analysis at the 5% level, the interaction between CM and MLA in column 1 is positive and significant, and the variable party match is negative and significant. Excluding party match and party match*MLA changes the magnitude of criminal, but does not change any of the other interactions, in fact, weakens them.

[81] I thank Siddharth George for sharing this data with me.

Table 3.I.24: Connections: Impact of Having Criminal Chief Minister

	(1)	(2)
Criminal	-0.180**	-0.148**
	(0.070)	(0.064)
Margin	0.055	0.003
	(0.940)	(0.937)
Criminal*Margin	2.888**	2.976**
	(1.264)	(1.200)
CM Criminal	-0.006	-0.008
	(0.044)	(0.047)
CM Criminal*MLA Criminal	0.071	0.027
	(0.047)	(0.052)
Party Match		-0.018
		(0.033)
Party Match*MLA Criminal		-0.118*
		(0.067)
Party Match*CM Criminal*MLA Criminal		0.171**
		(0.085)
Constant	1.283***	1.290***
	(0.051)	(0.054)
Police Station FE	Yes	Yes
Year FE	Yes	Yes
Week FE	Yes	Yes
Observations	503805	503805

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents regression discontinuity estimates of the impact of having a criminal politician in office on serious IPC crime at the weekly level. The dependent variable is transformed using the inverse hyperbolic sine transformation. The estimates are produced using a fixed effects regression at the police station level, with time fixed-effects. Mixed races within a bandwidth of 0.085 are included.

Table 3.I.25: Impact of Having Criminal Politician at the National Level

	(1)
Criminal	-0.140*
	(0.084)
Margin	-0.844
	(1.011)
Criminal*Margin	3.071**
	(1.530)
MP Criminal	-0.013
	(0.070)
MLA Criminal*MP Criminal	0.103
	(0.103)
Constant	1.290***
	(0.049)
Police Station FE	Yes
Year FE	Yes
Week FE	Yes
Observations	482091

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the original affidavits uploaded by the Election Commission. To verify the accuracy of the ADR-coded data, Prakash et al. (2019) re-enter the affidavits' data for the top two candidates from 2003 to 2007, and show that fewer than 3% of candidates changed from criminal to non-criminal or vice versa in the recoding. They also show that the number of crimes increased for about a quarter of candidates. This indicates that the ADR data accurately identifies criminality on the extensive margin but underestimates the total number of charges on the intensive margin. Since I do not use the number of charges throughout my study, except in this case, these results, which are also based on older data, do not affect my analysis.

CHAPTER 4

The Gap Within: Impact of Separate-Gender Polling Stations on Voter Turnout

Abstract

Governments in several countries create separate-gender polling stations to encourage female voting. Yet, little is known about the effectiveness of this policy. We estimate the impact of separate-gender polling stations on voter turnout using administrative data from the 2018 general election in Pakistan. We find that being assigned to separate-gender polling stations is associated with a reduction in turnout for both women and men by 2 and 1 percentage points respectively, when compared to the turnout of women and men in mixed-gender polling stations. Our results remain consistent after controlling for the role of resources, norms and mobility-related costs. Together, these results indicate that separate-gender polling stations do not alleviate gender-based voting constraints faced by women.

4.1 Introduction

There are large and persistent gender gaps in political participation in the developing world (Prillaman, 2017). Women are less likely to vote, run for office, campaign, canvass or make demands on those in government (Chhibber, 2002; Parthasarathy et al., 2017; Khan 2017). Female political participation could be hindered by gender-specific factors such as access to fewer resources, a 'gendered psyche', or the limited

mobilization of women (Burns et al., 2001; Fox and Lawless, 2010; Preece, 2016; Giné and Mansuri, 2018; Cheema et al., 2019; Iyer and Mani, 2019; Goyal, 2020). It could also be affected by non-gendered factors that affect both women and men. For example, additional costs imposed by administrative voting processes could have large effects on turnout (Downs, 1957; Brady and McNulty, 2011; de Kadt, 2017).

Governments in certain developing countries have adopted the use of separate-gender polling stations to encourage female voting (UN Women and United Nations Development Programme, 2015).[82] This policy aims to overcome constraints around safety and cultural norms faced by women by providing them with a separate space to vote. In cultures where women tend not to interact with unrelated men, having separate spaces to vote, with women staff and other facilities, is expected to increase access for women voters (UN Women and United Nations Development Programme, 2015). There is little evidence that the policy is effective in increasing female turnout.

In this paper, we study the impact of separate-gender polling stations on voter turnout using administrative data from the 2018 general elections in Pakistan. Comparing female turnout in separate-gender polling stations to female turnout in mixed-gender polling stations within a polling location, we find that separate-gender polling stations reduce female turnout by 2 percentage points.[83] A similar analysis for males shows that male turnout is reduced by 1 percentage point.

Our results also show that there is no heterogeneity in the response to separate-gender polling stations with respect to factors such as resources and norms at an aggregated level, including the role of education, awareness, mobility norms, bargaining power and partner's characteristics.

[82] Governments in Afghanistan, Algeria, Argentina, Chile, Ecuador, Egypt, Jordan, Kuwait, Lebanon, Mozambique, Pakistan, Sri Lanka, Zanzibar, among others, have adopted the use of separate-gender polling locations, polling stations and priority queues (Electoral Knowledge Network, 2013).

[83] A polling location is usually a government building, such as a school. In practice, multiple polling stations are often situated in the same polling location.

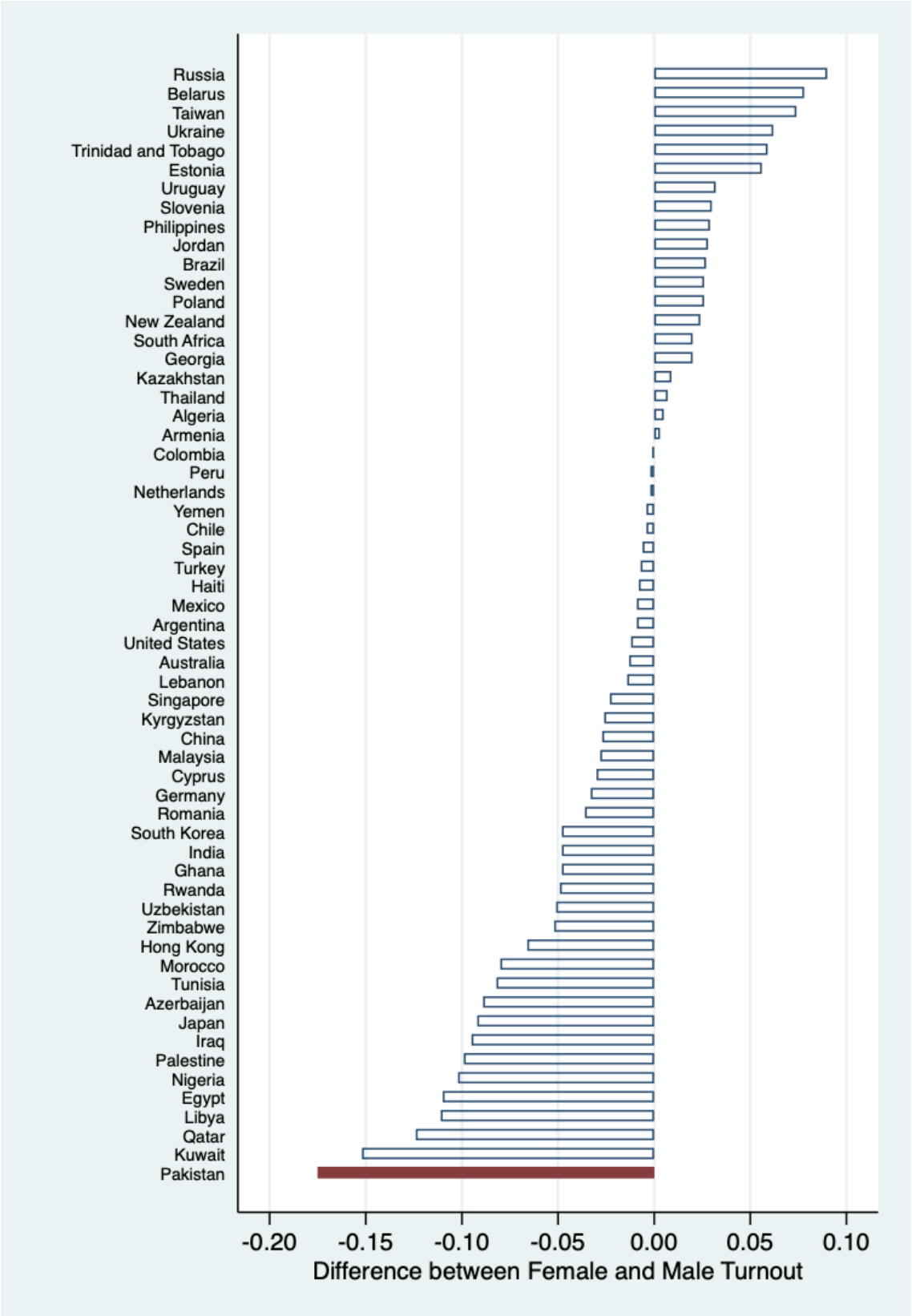
Our findings are important in understanding the constraints faced by women in voting - they suggest that the creation of separate-gender polling stations does not resolve the key constraint to low female turnout, and in fact, interacts with administrative, non-gendered constraints in a way that aggravates the turnout difference in separate-gender polling stations. Incorporating the effect of the interaction between gendered and non-gendered costs on female turnout could help better understand the constraints that prevent women and men from voting in separate-gender polling stations, such as a negative perception of separate-gender polling stations, or other norms that prevent women from voting alone. Understanding these barriers plays an important role in improving female turnout in developing countries.

4.2 Gender Gap and Creation of Polling Stations

The gap between male and female turnout in Pakistan is one of the highest in the world, and parts of the country face enormous resistance from men to women's voting (Figure 4.1). The Election Commission of Pakistan (ECP) has implemented the policy of separate-gender polling stations since the 2008 elections in order to encourage women's voting. Figure 4.2 shows that the gender turnout gap between males and females is large and persistent.

The ECP creates three kinds of polling stations – Female-Only, Male-Only, and Combined. The Female-Only and Male-Only polling stations are gender-specific, while Combined polling stations are mixed-gender. A polling station can be situated in any government building within the constituency, or when this is unavailable, in an improvised polling station on public property, or in a building owned by a private, registered educational institution. We define 'polling location' as a building within which one or multiple polling stations might be present. In practice, multiple polling stations are situated within a given polling location. For example, 'City District Government Junior Model School' is a government school in the city of Lahore

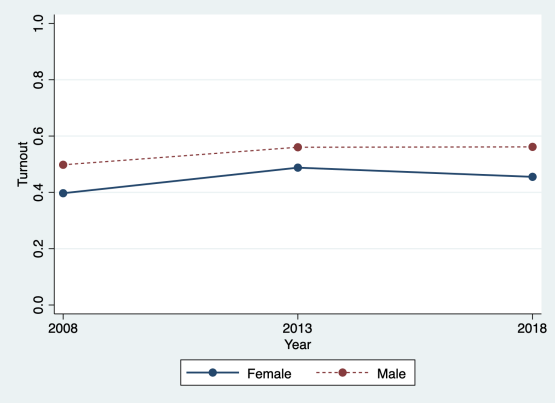
Figure 4.1: Pakistan has a Large Difference between Female and Male Turnout



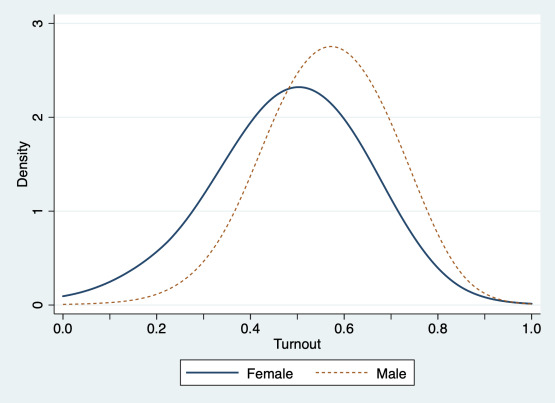
Notes: The graph uses self-reported likelihood of voting. It depicts the difference between the share of female and males in the country who report that they always vote. *Source:* Data from World Values Survey 2014 (Inglehart et al., 2014).

Figure 4.2: Gender Gap in Turnout in Pakistan

A. Persistent Gender Turnout Gap Elections



B. Higher Male Turnout in 2018



Notes: Panel A shows female and male turnout in Pakistan's general elections in 2008, 2013 and 2018. Polling station level turnout, disaggregated by gender, was made available for the first time in the 2018 election. Turnout rates for all elections are calculated using only separate-gender polling stations for consistency. Panel B shows the distributions of female and male turnout at the polling station level in Pakistan's 2018 general elections. *Panel A Source:* Free and Fair Election Network 2009, 2013, 2018a.

that had 5 polling stations in the 2018 election (2 Female-Only, 2 Male-Only and 1 Combined). Here, 'City District Government Junior Model School' is the polling location. The 2018 election dataset has 79,091 unique polling stations and 61,548 unique polling locations. Table 4.1 provides a distribution of polling locations with different combinations of separate- and mixed-gender polling stations. Table 4.2 provides the distribution of polling stations for the 2018 election by polling station type. This table shows that both separate- and mixed-gender polling stations form approximately half of the polling stations across the country.

We refer to internal ECP documents that dictate the policy on creating polling stations. In preparing the polling scheme, the ECP allocates polling stations by census blocks. Here, four considerations are essential. First, where separate-gender polling stations are created, corresponding Male-Only and Female-Only polling stations are to be within the same polling location, as far as possible (Election Commission of Pakistan, 2018). Where this is not possible, Male-Only polling stations might be placed in a different polling location than Female-Only polling stations. Second, where Combined polling stations are created, corresponding male and female voters

Table 4.1: Distribution of Polling Locations with Different Polling Station

		Number of Separate-Gender Polling Stations			
		0	1	2	3+
Number of Mixed-Gender Polling Stations	0		33.49%	10.26%	1.52%
	1	47.57%	0.72%	0.63%	0.11%
	2	3.94%	0.06%	0.09%	0.03%
	3+	0.67%	0.01%	0.03%	0.01%

Notes: This table presents the distribution of polling locations with different polling station combinations. There are a total of 61,548 polling locations. 536 polling locations do not have information on polling station type (0.87% of total polling locations). Hence the sum of the percentages in this table is 99.13%.

Table 4.2: Distribution of Polling Station Types

Polling Station Type	**Frequency**	**Share**
Combined	38,009	48%
Female-Only	19,424	25%
Male-Only	21,081	27%
Unknown	577	1%
Total	**79,091**	**100%**

Notes: The table presents the share of Male-Only, Female-Only and Combined polling stations in the 2018 election dataset. There are a total of 79,091 polling stations in the dataset with less than 1% observations that do not have information about the polling station type.

of a census block are to be assigned to be same Combined polling station (Election Commission of Pakistan 2018). Third, as far as possible, the ECP ensures that the distance between the polling station and the voters assigned to it is less than 1 kilometre (Government of Pakistan, 2017). This radius was adhered to in practice - a post-election assessment of polling stations found that 94 percent of surveyed individuals said that the distance between the polling stations and their place of residence was less than 1 km (Free and Fair Election Network, 2018b). Finally, no more than 1,200 voters can be assigned to any polling station (Government of Pakistan, 2017).[84] The last census for Pakistan prior to the 2018 election was conducted in 1998, which means that little updated socio-economic information was available at the time of preparing the polling scheme.[85]

In practice, the ECP attempts to create polling stations that satisfy these four considerations within resource constraints. There are two important resource constraints that play an important part in designing the polling scheme. First, the availability of government buildings and resources (such as infrastructure and election budget) determines the number of polling stations in one location, the number of voters assigned to a particular polling stations in a given area and the distance of residents from polling stations. For instance, if a particular locality with a large population just has one government building or other appropriate public property or private property, the ECP will either have to create multiple polling stations in the government building or increase the number of voters assigned to each polling station beyond 1,200 if making additional polling stations is costly. This will also have consequences for the distance between residents and polling stations.

Second, the availability of trained female staff determines whether separate-gender polling stations can be made. If a particular locality does not have trained female polling staff, then the ECP may opt for a Combined polling station. The

[84]The final implementation of the policy in Pakistan is dictated by the availability of resources, such as female staff, etc.

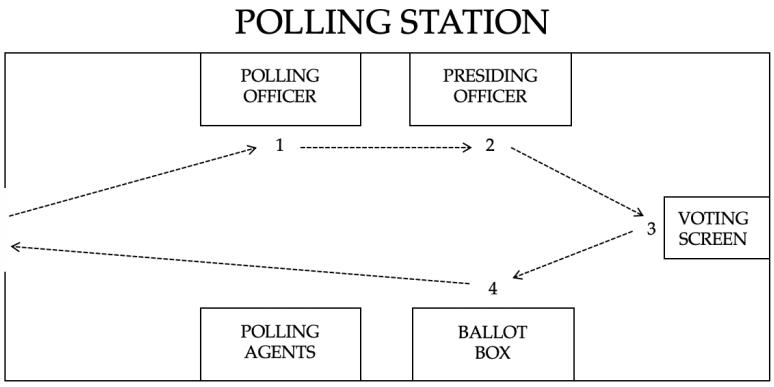
[85]The allocation of voters to their polling stations is known in advance, and cannot be changed.

resource constraint plays an important role in determining the number of separate- and mixed-gender polling stations made.

Once the number of polling stations, their size and location are determined, the last step is to assign census blocks to polling stations. Here, a census block is either assigned to a Combined polling station or split up and assigned to Female-Only and Male-Only polling stations. Census blocks and polling stations have an average of 457 and 1,268 registered voters respectively. Hence, one polling station on average has voters from several census block codes. To the best of our knowledge, there is no criteria used to assign census blocks to separate- or mixed-gender polling stations.

The voting process once a voter enters a polling station is shown in Figure 4.3. Further details are given in the Appendix 4.B.

Figure 4.3: Voting Process in the 2018 General Election



Explanation: 1. Individual enters polling station with original national identity card. Polling officer verifies identity and informs polling agents. 2. Presiding officer hands ballot paper to individual. 3. Individual puts stamp on ballot paper for the candidate she/he wishes to vote for behind the voting screen. 4. Individual places ballot paper with stamp inside ballot box. 5. Individual exits the polling station.

4.3 Data

In this paper, we use an administrative dataset with polling station-level electoral information for Pakistan's most recent general election conducted on 25 July 2018

(Sonnet, 2019).[86] There are a total of 79,091 unique polling stations in the data, divided into the three types of polling stations - Female-Only, Male-Only and Combined. 48% of the total 79,091 polling stations are mixed-gender, 25% are Female-Only and 27% are Male-Only. Gender-disaggregated turnout data is available for all three polling station types.

The number of observations in the dataset is nearly twice the number of polling stations. This is because the election in 2018 was conducted at both the national and provincial levels. Individuals voted for both a National Assembly and a Provincial Assembly seat in their polling stations. As a result, polling stations are duplicated for National and Provincial Assembly seats.

We combine this data with the 2015 Pakistan Social and Living Standards Measurement (PSLM) and the 2017 Demographic and Health Survey (DHS) to analyse mechanisms. The 2015 PSLM and the 2017 DHS are representative at the district and national levels, respectively, and contain information on income, employment, education, amongst other development outcomes.[87]

4.4 Methodology and Results

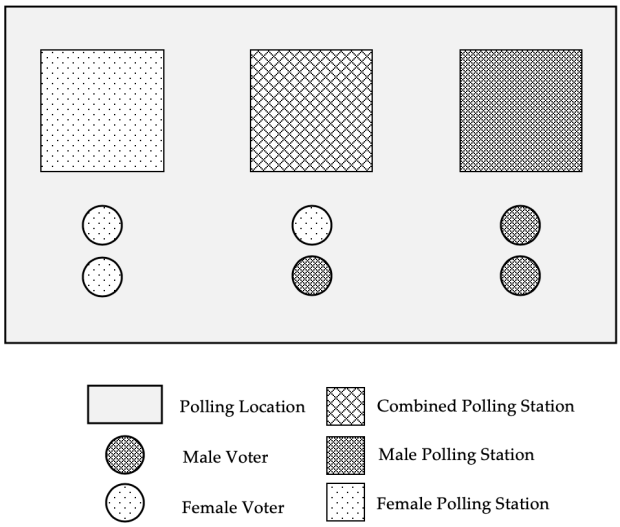
To estimate the impact of polling station type on voter turnout, we compare the turnout of a particular gender in a separate-gender polling station to the turnout of the same gender in a mixed-gender polling station (Figure 4.4). Since there can be multiple polling stations within the same location or building, for example, a school, we control for the polling location, hence, comparing only separate-gender and mixed-gender polling stations within a polling location.[88]

[86]Election results data at the polling station level, disaggregated by gender, is not available for previous national elections. Hence, we could not use a panel dataset for our analysis.

[87]The 2015 PSLM was conducted by the Pakistan Bureau of Statistics (PBS, 2016) which has made the micro-files for the survey publicly available on their website (`www.pbs.gov.pk`). The DHS is conducted by USAID in countries across the world.

[88]To identify the polling station location, we clean the names of all polling stations and then group polling stations with the same names together. Hence, we are able to control for location

Figure 4.4: Illustration of Main Empirical Specifications



Explanation: This figure illustrates our preferred empirical specification which controls for polling location. In Equation 4.1, we compare the female voter turnout in a Female-Only polling station with the female voter turnout in a Combined polling station within the *same polling location*. Similarly, we compare male voter turnout in a Male-Only polling station with male voter turnout in a Combined polling station within the *same polling location*.

The empirical specification used to estimate this impact is given in Equation 4.1, which is our preferred specification. Here, $FemaleTurnout_{ijc}$ is the turnout of females in polling station i, polling location j and constituency c.[89] $Female_{ijc}$ is a dummy variable that takes the value 1 if polling station i is a Female-Only polling station, and 0 if it is a Combined polling station. μ_c and γ_{ij} represent the constituency and location fixed effects, respectively.[90] In addition to this preferred specification, we also show results for a simple OLS that does not control for constituency and/or location. We conduct a similar analysis for males.

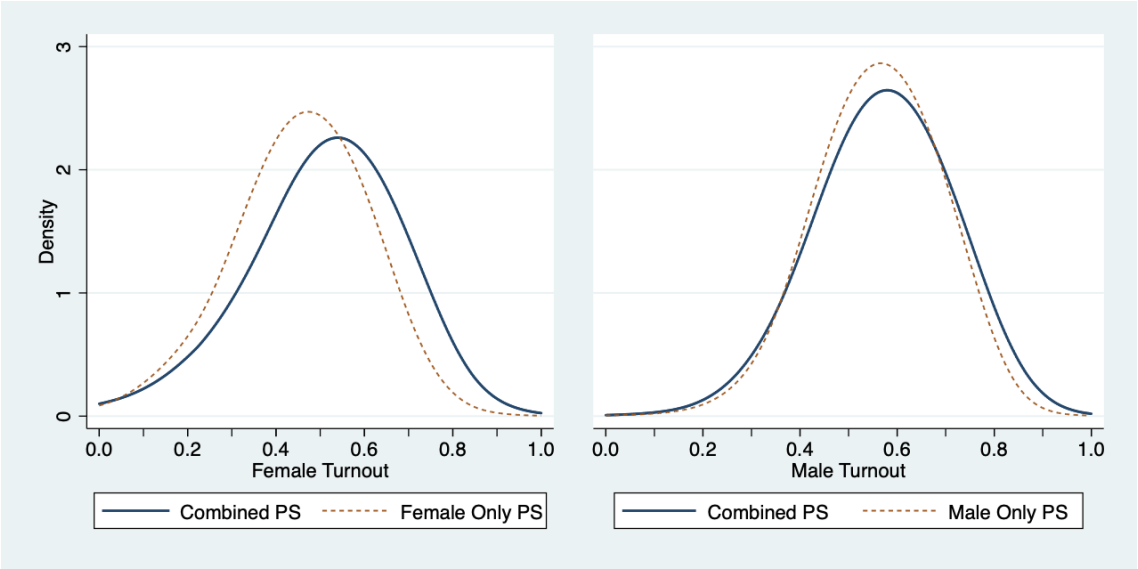
$$FemaleTurnout_{ijc} = \beta_0 + \beta_1 Female_{ijc} + \mu_c + \gamma_{ij} + \epsilon_{ijc} \tag{4.1}$$

fixed effects. 3.77% of all polling stations are in locations that have at least one mixed-gender and at least one separate-gender polling station (2,982 polling stations out of a total of 79,091).

[89]Turnout is defined as the total number of votes cast on election day as a proportion of the total number of registered voters.

[90]In this context, provincial and national elections are held at the same time. Individuals may cast votes for either provincial or national, or both elections at their polling station. Our constituency fixed effects control for national and provincial seats separately.

Figure 4.5: Combined Polling Stations Have Higher Turnout than Separate-Gender Ones



Notes: The graph shows the polling station-level distributions of turnout in mixed and separate-gender polling stations for females and males in Pakistan's 2018 general elections.

It is important to highlight that the incorporation of location fixed effects significantly reduces the variation in the sample that the results rely on. This is because the results from the preferred specification with location fixed effects are from polling stations that have at least one mixed-gender and at least one separate-gender polling station in the same polling location, which represents only 3.77% of total polling stations and 1.69% of total polling locations in the dataset. In other words, the results with location fixed effects are driven by a total of 2,982 polling stations and 1,039 polling locations in the dataset. We acknowledge that this an important caveat to the results from our preferred specification. To mitigate this risk, we provide the results with and without the incorporation of location fixed effects. As can be seen from Table 4.3, the results with and without the incorporation of location fixed effects are in a similar direction which increases our confidence in the findings.

Column (3) in Table 4.3, which presents results from our preferred specification, shows that Female-Only polling stations are associated with a reduction in female turnout by 2 percentage points, on average, when compared to Combined polling stations. Male-Only polling stations are associated with a reduction in male turnout by 0.9 percentage points on average when compared to Combined polling stations. The results remain consistent across all three specifications presented.

4.4.1 Threats to Identification

The ECP creates polling stations across the country based on several factors such availability of infrastructure, number of registered voters, availability of female staff etc. Hence, a simple comparison between the turnout in separate- and mixed-gender polling stations faces several threats to identification. This is because of possible omitted variable bias where the type of polling station might be correlated with some other factor that could explain the difference between the turnout in separate- and mixed-gender polling stations. For instance, it might be the case that there

Table 4.3: Lower Turnout in Separate-Gender Polling Stations

Panel A: Female Turnout in Female-Only vs Combined Polling Stations

Dep Var: Female Turnout	(1)	(2)	(3)
Female Only PS	-0.056***	-0.054***	-0.020***
	(0.001)	(0.001)	(0.006)
Observations	69303	69303	69303
Adjusted R^2	0.036	0.542	0.932
Constituency Fixed Effects	No	Yes	Yes
Location Fixed Effects	No	No	Yes

Panel B: Male Turnout in Male-Only vs Combined Polling Stations

Dep Var: Male Turnout	(1)	(2)	(3)
Male Only PS	-0.011***	-0.020***	-0.009**
	(0.001)	(0.001)	(0.004)
Observations	72370	72370	72370
Adjusted R^2	0.003	0.465	0.878
Constituency Fixed Effects	No	Yes	Yes
Location Fixed Effects	No	No	Yes

Notes: This table measures the impact of having separate-gender polling stations on turnout. Panel A compares the female turnout in Female-Only polling stations with that in Combined polling stations. Panel B compares the male turnout in Male-Only polling stations with that in Combined polling stations. Column (1) conducts a simple OLS regression. Column (2) controls for constituency fixed effects. Column (3) controls for location fixed effects. Each location has one national assembly and one provincial assembly constituency. Standard errors are clustered at the location level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

are more mixed-gender polling stations in urban areas, which have different socio-demographic characteristics when compared to rural areas. In this case, the results might be driven by the socio-demographic characteristics and would not capture the impact of the polling station type.

The empirical strategy of this paper relies on location fixed effects to mitigate the threat of omitted variables. By introducing location fixed effects, the paper compares female turnout in Female-Only polling stations with female turnout in Combined polling stations within a polling location, which is typically a government building. It is also important to mention that the ECP ensures that voters reside within 1km of the polling station - 94 percent of surveyed individuals said that the distance between the polling stations and their place of residence was less than 1 km for the 2018 election (Free and Fair Election Network, 2018b). This means that the empirical strategy of this paper compares females assigned to separate- and mixed-gender polling stations within a 1km radius. This helps mitigate the threat of omitted variables.

One threat to identification may still remain after incorporating location fixed effects - it might be the case that even within a 1km radius, the characteristics of voters assigned to different polling stations are different. We acknowledge this potential threat to inference. Our identifying assumption is that the allocation of voters to polling stations is conditionally random within these narrowly-defined locations. While we cannot test this assumption directly at present, because the data for Pakistan's census conducted in 2018 has not been released and the census before 2018 was conducted in 1998, we believe that this is a reasonable assumption since the characteristics of voters within these 1km radius locations are likely to be similar across polling stations. Furthermore, since there was no recent census data available to the government when designing the polling scheme, it would have been difficult for them to systematically assign voters to polling stations differentially. When the 2018 census data is publicly released, we will be able to test this assumption directly.

4.5 Mechanisms

To understand the mechanisms that could drive these results, we look at the role of various gendered and non-gendered factors that determine turnout and are identified in the literature. First, we test the role of factors that discourage women's voting, such as lack of access to resources or information (Burns et al., 2001; Giné and Mansuri, 2018). We use measures of education and awareness to test the role of this factor. Second, we test the role of social norms that reinforce a 'gendered psyche' (Fox and Lawless, 2010; Preece, 2016; Gottlieb, 2016; Cheema et. al, 2019). We use district-level measures of female mobility-related norms, and female bargaining power to test this channel. Finally, we look at the role of voting costs, such as the ability for males and females of a household to be able to vote in the same polling location (Downs, 1957; Brady and McNulty, 2011).

We use 30 variables from the 2015 Pakistan Social and Living Standards Measurement survey (PSLM) and from the 2017 Demographic and Health Survey (DHS) to test the role of resources and norms. In the interest of conciseness and power, these variables are aggregated at the district level, and combined into seven indices, following Anderson (2008). The seven indices of interest are male and female education, male and female awareness, mobility, bargaining power, and husband's characteristics.[91] The variables used to construct the indices are shown in Table 4.4.

Higher levels of education or awareness might mean that individuals are more politically involved or active. Politically inclined individuals, in turn, might be more likely to vote and, hence, less likely to be affected by the policy of separate polling stations. Lower female bargaining power, or less equitable mobility and gender norms could be important if the policy of separate-gender polling stations encourages females in conservative areas to vote, especially if the demand for separate-gender polling stations comes from the women in conservative areas themselves. Alternatively, it

[91] The results for the individual variables are consistent with the indices.

might have the opposite impact if the demand for this policy does not represent the constraints faced by the women. Finally, the characteristics of husbands might have an impact on women's constraints. For instance, more educated husbands might be associated with higher mobility of their wives. Detailed information on the definitions of the variables can be found in Appendix 4.C.

We test the role of various indices in explaining the results by running the empirical specification in Equation 4.2. Here, $FemaleTurnout_{ijdc}$ is the female turnout in polling station i, polling location j, constituency c and district d. $Index_d$ represents the district level value of the index variable explained above. We run a similar analysis for males. With the inclusion of location fixed effects, the interaction term $Female_{ijcd} * Index_d$ compares polling locations across districts with higher and lower values of the respective index. This helps us check whether the type of polling station is associated with differential turnout as the index changes across districts.

$$FemaleTurnout_{ijcd} = \beta_0 + \beta_1 Female_{ijcd} + \beta_2 Female_{ijcd} * Index_d + \mu_c + \gamma_{ij} + \epsilon_{ijcd} \quad (4.2)$$

We also examine the costs of voting or mobility-related costs, by testing whether males and females being able to vote together drives the results. When mixed-gender polling stations are created, an entire census block with all its females and males is assigned to that polling station. However, when the ECP creates separate-gender polling stations, a census block is divided into two polling stations, one for females and one for males. While the corresponding female and male polling stations may be located in the same polling location, this is not always the case. Combining our data with information on the assignment of census blocks to polling stations shows that where blocks are allocated into gender-specific polling stations, only 32 percent of the corresponding Male-Only and Female-Only polling stations are in the same polling location.

Table 4.4: Summary of Indices Used for Analysis

#	Index	Types of Variables Used
1	Education	Female and male ability to read, school attendance, highest level of education attained
2	Awareness	Female and male consumption of newspapers, TV, radio, mobile and internet
3	Mobility	Norms against free mobility of women, including the need for permission to go to a doctor and acceptability of being hit for not taking permission
4	Bargaining Power	Decision-making power of women in different household decisions, including the use of contraception and household spending
5	Husband	Husband's education and labour force participation

Notes: This table provides a brief summary of the different indices created to various mechanisms. The Education Index uses data from the Pakistan Social and Living Standards Measurement survey conducted in 2015. All other indices use data from the Demographic and Health Survey conducted in 2017. For further details about the indices, please refer to the Appendix 4.C.

We test the role of mobility-related characteristics by computing the variable $Corresp\ Male_{ij}$, which tells us the share of all block codes in the polling station that are assigned to the same polling location for males. The coefficient on the interaction term $Female_{ij} * CorrespMale_{ij}$ tells us whether the difference in female turnout in Combined and Female-Only polling stations is different when corresponding Male-Only polling stations are in the same polling location. We run a similar analysis for males.

$$FemaleTurnout_{ijc} = \beta_0 + \beta_1 Female_{ijc} + \beta_2 Female_{ijc} * CorrespMale_{ij} + \mu_c + \gamma_{ij} + \epsilon_{ijc} \tag{4.3}$$

The results of the aforementioned analysis (Table 4.5) shows that the interaction terms are statistically insignificant at the 10 percent level. This implies that districts with different values of various indices have a similar association between the type of polling station and turnout. The statistically insignificant results for 'Female*Corresponding Male' and 'Male*Corresponding Female' show that the re-

sults are not being driven by females and males wanting to vote together in the same polling location. By ruling out several potential mechanisms, the analysis tentatively point towards the possibility of the results being driven by a feature of separate- or mixed-gender polling stations that is common throughout the country and does not vary by norms, resources or voting together.

4.6 Discussion and Conclusion

Together, these results suggest that separate-gender polling stations do not address the gender-based constraints to voting. To be effective, the policy of separate-gender polling stations would overcome the resource-, norms- or mobilization-based constraints faced by women that are highlighted in the literature. Having separate spaces for women to vote, could in theory, address the 'gendered psyche' by reducing men's resistance to female voting, or making women feel more comfortable in the public sphere. However, our analysis shows that separate-gender polling stations do not alleviate such constraints.

Instead, our results suggest that separate-gender polling stations increase non-gendered costs of voting for both females and males, and consequently, reduce turnout of both genders. Our analysis shows that the results are consistent across different levels of education, awareness, female bargaining power, and mobility norms in the country. This suggests that the results are driven by a feature of these polling stations in themselves. The administrative implementation of the policy of separate-gender polling stations could interact with the gendered component of the policy, and consequently, have large effects on turnout. While we can control for the effects of placement of separate-gender polling stations by looking at within-polling location differences, there might be other systematic differences in the manner this policy is implemented, in terms of staff or other resources made available to separate-gender polling stations, or in terms of the general or historical perceptions of such polling

Table 4.5: Results are Consistent after Including Role of Resources, Norms, Voting Together

Panel A: Female Turnout in Female-Only vs Combined Polling Stations

Dep Var: Female Turnout	(1)	(2)	(3)	(4)	(5)	(6)
Female Only PS	-0.024***	-0.020***	-0.021***	-0.020***	-0.021***	-0.021***
	(0.009)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
Female*Corresponding Male	0.005					
	(0.008)					
Female*Education Index		0.000				
		(0.009)				
Female*Awareness Index			0.005			
			(0.018)			
Female*Mobility Index				-0.001		
				(0.012)		
Female*Bargaining Power Index					-0.018	
					(0.021)	
Female*Husband Index						0.005
						(0.012)
Observations	69303	68293	44692	44692	44692	44692
Adjusted R^2	0.932	0.931	0.937	0.937	0.937	0.937
Constituency Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Male Turnout in Male-Only vs Combined Polling Stations

Dep Var: Male Turnout	(1)	(2)	(3)
Male Only PS	-0.011**	-0.010**	-0.008
	(0.005)	(0.005)	(0.005)
Male*Corresponding Female	0.003		
	(0.006)		
Male*Education Index		0.002	
		(0.006)	
Male*Awareness Index			0.004
			(0.011)
Observations	72370	71273	47026
Adjusted R^2	0.878	0.874	0.871
Constituency Fixed Effects	Yes	Yes	Yes
Location Fixed Effects	Yes	Yes	Yes

Notes: This table tests for potential mechanisms. All specifications control for constituency and location fixed effects. Each location has one national assembly and one provincial assembly constituency. Standard errors are clustered at the location level and are reported in parentheses. For a detailed description of the indices, please refer to the Appendix 4.C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

stations.

Our research opens up three avenues for future work. First, it is important to understand whose preferences the policy of separate-gender polling stations represents. It might be the case that this policy is being driven by demands from men or policymakers, rather than addressing the actual constraints faced by women.

Second, further research is required to understand the exact administrative features of separate-gender polling stations that decrease female and male turnout. Systematic differences in implementation could have a large impact on electoral outcomes (Neggers, 2018). Future work could help uncover the mechanisms at play, which would help our understanding of the administrative determinants of voter turnout in developing countries.

Finally, future research could test the effectiveness of this policy in other contexts where it is implemented. It might be the case that the impact of this policy in conflict-affected areas such as Afghanistan and Yemen is different from its impact in places where the implementation is driven by concerns regarding women's safety or harassment by men, for example, or where it is driven by cultural and religious norms.

Understanding the impact of the policy of creating separate-gender polling stations on women's turnout behaviour is important for governments and electoral bodies around the world. It can help design policies that encourage the participation of women in the political arena and lead to better outcomes for all.

References

Anderson, Michael L., "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects," *Journal of the American Statistical Association*, 2008, *103* (484), 1481–1495.

Brady, Henry E. and John E. McNulty, "Turning Out to Vote: The Costs of Finding and Getting to the Polling Place," *American Political Science Review*, 2011, *105* (1), 115–134.

Burns, Nancy, Kay Lehman Schlozman, and Sidney Verba, *The Private Roots of Public Action: Gender, Equality, and Political Participation*, Cambridge, MA: Harvard University Press, 2001.

Cheema, Ali, Sarah Khan, Shandana Khan-Mohmand, and Asad Liaqat, "Canvassing the Gatekeepers: A Field Experiment to Increase Women's Electoral Turnout in Pakistan," *Working Paper*, 2019.

Chhibber, Pradeep, "Why are Some Women Politically Active? The Household, Public Space, and Political Participation in India," *International Journal of Comparative Sociology*, 2002, *43* (3-5), 409–429.

de Kadt, Daniel, "Bringing the Polls to the People: How Electoral Access Encourages Turnout But Exacerbates Political Inequality," Technical Report SSRN 2922125, Social Science Research Network, Rochester, NY 2017.

Downs, Anthony, "An Economic Theory of Political Action in a Democracy," *Journal of Political Economy*, 1957, *65* (2), 135–150. Publisher: University of Chicago Press.

Election Commission of Pakistan, "Preparation of Polling Scheme for General Elections - 2018 (Order No. F. 7(1)/2018 - Cord)," 2018.

Electoral Knowledge Network, "Systems with Separate Polling Stations for Men and Women," 2013.

Fox, Richard L. and Jennifer L. Lawless, "If Only They'd Ask: Gender, Recruitment, and Political Ambition," *The Journal of Politics*, 2010, *72* (2), 310–326.

Free and Fair Election Network, "Pakistan General Elections 2008: Election Observation Summary and Recommendation for Electoral Reforms," Technical Report, Islamabad, Pakistan 2009.

_ , "General Election 2013 - FAFEN Observation," Technical Report, Islamabad, Pakistan 2013.

_ , "Analysis of Voter Turnout in GE-2018," Technical Report, Islamabad, Pakistan 2018a.

_ , "General Election 2018 Polling Stations Assessment Report," Technical Report, Islamabad, Pakistan 2018b.

Giné, Xavier and Ghazala Mansuri, "Together We Will: Experimental Evidence on Female Voting Behavior in Pakistan," *American Economic Journal: Applied Economics*, 2018, *10* (1), 207–235.

Gottlieb, Jessica, "Why Might Information Exacerbate the Gender Gap in Civic Participation? Evidence from Mali," *World Development*, 2016, *86*, 95–110.

Government of Pakistan, "Elections Act," 2017.

Goyal, Tanushree, "How Women Mobilize Women Into Politics: A Natural Experiment in India," *SSRN Electronic Journal*, 2020.

ICF, "Demographic and Health Surveys Standard Recode Manual for DHS7," Technical Report, Rockville, Maryland, USA 2018.

Inglehart, R., C. Haerpfer, A. Moreno, C. Welzel, K. Kizilova, J. Diez-Medrano, M. Lagos, P. Norris, E. Ponarin, and B. Puranen, "World Values Survey: Round Six - Country-Pooled Datafile," 2014.

Iyer, Lakshmi and Anandi Mani, "The Road not Taken: Gender Gaps along Paths to Political Power," *World Development*, 2019, *119*, 68–80. Publisher: Elsevier Ltd.

Khan, Sarah, "What Women Want: Gender Gaps in Political Preferences," in Matt Golder and Sona Golder, eds., *Symposium: Women/Gender and Comparative Politics. CP: Newsletter of the Comparative Politics Organized Section of the American Political Science Association.*, Vol. 27(1) 2017, pp. 42–49.

Neggers, Yusuf, "Enfranchising Your Own? Experimental Evidence on Bureaucrat Diversity and Election Bias in India," *American Economic Review*, 2018, *108* (6), 1288–1321.

Pakistan Bureau of Statistics, "Pakistan Social And Living Standards Measurement Survey (PSLM) 2014-15: Provincial/District Dataset," Technical Report, Islamabad, Pakistan 2016.

Parthasarathy, Ramya, Vijayendra Rao, and Nethra Palaniswamy, "Deliberative Inequality: A Text-As-Data Study Of Tamil Nadu's Village Assemblies," Policy Research Working Papers 8119, The World Bank 2017.

Preece, Jessica Robinson, "Mind the Gender Gap: An Experiment on the Influence of Self-Efficacy on Political Interest," 2016, *12* (1), 198–217.

Prillaman, Soledad Artiz, "Strength in Numbers: How Women's Groups Close India's Political Gender Gap," *Working Paper*, 2017, p. 71.

Sonnet, Luke, "2018 Pakistani General Election Polling Station [Dataset]," 2019.

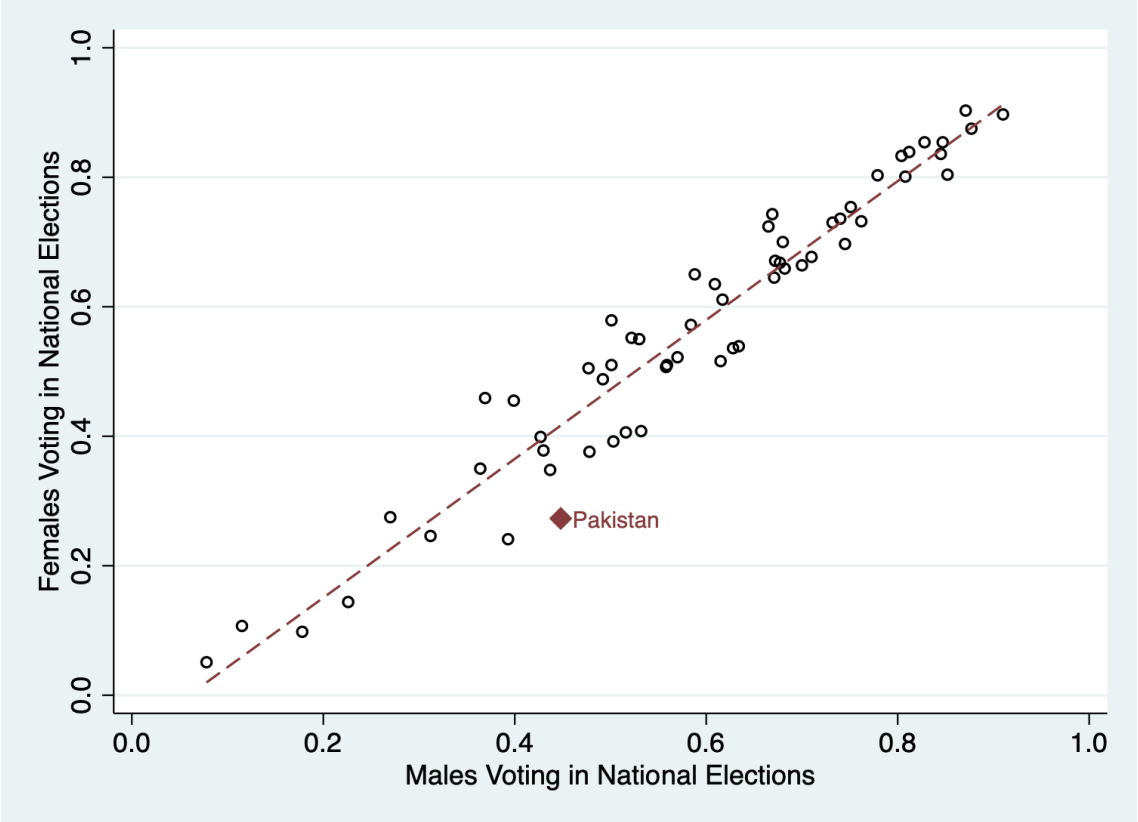
UN Women and United Nations Development Programme, "Inclusive Electoral Processes: A Guide for Electoral Management Bodies on Promoting Gender Equality and Women's Participation," Technical Report 2015.

Appendix

4.A Gender Turnout Gap

Figure 4.A.1 presents a scatter plot of the average share of females and males in the country who say they always vote. While males are more likely to vote compared to females in several countries, Pakistan remains an outlier with one of the largest gender turnout gaps in the world.[92]

Figure 4.A.1: Males are More Likely to Vote in National Elections than Females



Notes: The graph uses self-reported answers on the likelihood of voting. It shows the percentage of males and females who report that they always vote. The dashed line is the line of best fit. *Source:* World Values Survey, 2014

[92] While survey data such as the one used here runs the risk of over-reporting turnout, it allows us to make cross-country comparisons.

4.B Voting Process

The voting process for the 2018 general election in Pakistan is given in the Elections Act 2017. On election day, voters are required to bring their original national identification card (CNIC) for identity verification.[93] No other form of identification (e.g. passport, drivers license) is accepted. Individuals can vote with their original CNIC even if it has expired. Women and men usually have separate waiting queues in Combined polling stations.

Upon entering the polling station, individuals are required to go to the desk of the polling officer and present their CNIC. The polling officer will verify the details of the individual given on the CNIC with a list of registered voters. The individual is required to show her/his face so that the polling officer can verify their identity. If the name of the individual is present in the voter list, then the polling officer will call out the name and the serial number of the voter in the voting list out loud so that the polling agents seated close by can hear this and keep a track of the voters on their list. Each candidate can assign two polling agents per polling station. The polling agents represent the candidates and act as a check on the administrative staff. Then the polling officer will mark the right thumb of the individual with indelible ink which serves as a visual identifier of having voted. After this, the polling officer will ask the individual to place a thumb print on the voter list which is proof that the individual voted.

Once the polling officer has crossed off the individuals name from the voter list, the individual will then move towards the adjacent desk where the assistant presiding officer will hand over the ballot paper after taking a thumb print as receipt, and stamping the back of the ballot paper.[94] The assistant presiding officer will give the individual a stamp and keep her/his CNIC. Then the individual goes behind the

[93] Copies of the CNIC are cannot be used for identity verification.

[94] The are two assistant presiding officers, one for the national assembly seat and one for the provincial assembly seat. Both hand over separate ballot papers for both seats to the individual.

voting screen to mark a stamp on the candidate that the individual wants to vote for. After this, the individual will return the stamp to the presiding officer, collect the CNIC, and put the voting ballot paper in the ballot box.[95]

[95]There are two ballot boxes, one for the national assembly and one for the provincial assembly.

4.C Index Definitions and Descriptions

4.C.1 Female Indices

Education Index: Education could be an important mechanism that could help explain the main results. To test this channel, we created an Education Index using three education-related variables from the 2015 Pakistan Social and Living Standards Measurement survey (PSLM), namely, $Read_d$, $Attend_d$ and $Level_d$. $Read_d$ is the percentage of women in district d who know how to read, $Attend_d$ is the percentage of women in district d who have attended school and $Level_d$ is the average highest grade/level of education for women in district d. These three variables are used to create the Education Index for district d and combined with the administrative data of the 2018 election results.

Awareness Index: We create an Awareness Index using six variables from the 2017 Demographic and Health Survey, namely, $News_d$, $Radio_d$, TV_d, $Mobile_d$, $Internet_d$ and $InternetUsage_d$. $News_d$ is the percentage of women who read the news at least once a week in district d. $Radio_d$ is the percentage of women who listen to the radio at least once a week, TV_d is the percentage of women who watch TV at least once a week, $Mobile_d$ is the percentage of women who own a mobile phone, $Internet_d$ is the percentage of women who have used the internet at least once in a year and $InternetUsage_d$ is the percentage of women who have used the internet at least once in the last week. These six variables are used to create the Awareness Index for district d and combined with the administrative data of the 2018 election results.

Mobility Index: To test how female mobility and the norms around female mobility might explain the main results, we create a Mobility Index. For this purpose, we extract three mobility-related variables from the 2017 Demographic and Health Survey for Pakistan, namely, $Permission_d$, $Beating_d$ and $Alone_d$. $Permission_d$ is

the percentage of married women in district d who report that getting permission from their partners to go to the doctor will be a problem. $Beating_d$ is the percentage of women in district d who believe that it is okay for their partner/husbands to hit them if they go outside without getting permission from their partner/husband. $Alone_d$ is the percentage of women in district d who report that wanting to go alone to the doctor would be a big issue. These three variables are used to create the Mobility Index for district d and combined with the administrative data of the 2018 election results.

Bargaining Power Index: We create the Bargaining Power Index by using seven variables from the 2017 Demographic and Health survey. $HusDecidesCont_d$ is the percentage of women whose husbands exclusively decide the use of contraceptives in district d, as a proxy for decision-making within the household. $HusDecidesNoCont_d$ is the percentage of women who report that their husbands exclusively decide not to use contraceptives, $OthersDecideHealth_d$ is the percentage of women who do not have a role in the decision about their own health, $OthersDecidePurchase_d$ is the percentage of women who do not have a role in making the decision about household purchases, $OthersDecideVisit_d$ is the percentage of women who do not have a role in making the decision about visiting relatives and $HusbandMoney_d$ is the percentage of women who have no role in making the decision about the way their husband's money is spent. $Worked_d$ is the percentage of women who did not work in the last 12 months. These seven variables are used to create the Bargaining Power Index for district d and combined with the administrative data of the 2018 election results.

Husband Index: We test the channel of husband's characteristics to see if it might help explain the main results for females. We test this channel by creating a Husband Index using two variables from the 2017 Demographic and Health survey, namely, $HusbandEdu_d$ and $HusbandWork_d$. $HusbandEdu_d$ is the average highest level of husband's education in district d. $HusbandWork_d$ is average percentage of

husbands who worked in the last 12 months. These two variables are used to create the Husband Index for district d and combined with the administrative data of the 2018 election results.

4.C.2 Male Indices

Education Index: Similar to females, we also create an Education Index for males to test for underlying mechanisms. The Education Index for males uses three education-related variables from the 2015 Pakistan Social and Living Standards Measurement survey (PSLM), namely, $Read_d$, $Attend_d$ and $Level_d$. $Read_d$ is the percentage of men in district d who know how to read, $Attend_d$ is the percentage of men in district d who have attended school and $Level_d$ is the average highest grade/level of education for men in district d. These three variables are used to create the Education Index for district d and combined with the administrative data of the 2018 election results.

Awareness Index: We create an Awareness Index for males to test the awareness channel. The index uses six variable from the 2017 Demographic and Health Survey, namely, $News_d$, $Radio_d$, TV_d, $Mobile_d$, $Internet_d$ and $InternetUsage_d$. $News_d$ is the percentage of men who read the news at least once a week in district d. $Radio_d$ is the percentage of men who listen to the radio at least once a week, TV_d is the percentage of men who watch TV at least once a week, $Mobile_d$ is the percentage of men who own a mobile phone, $Internet_d$ is the percentage of men who have used the internet at least once in a year and $InternetUsage_d$ is the percentage of men who have used the internet at least once in the last week. These six variables are used to create the Awareness Index for district d and combined with the administrative data of the 2018 election results.

4.D Data

A summary of the different sources of data used in this paper and their use is given in Table 4.D.1.

Table 4.D.1: Data Sources Used for Analysis

#	Source	Description	Use
1	Administrative Election Results Data (2018)	Dataset with the 2018 election results at the polling station level	Produce the main results of the paper showing the impact of separate gender polling stations on turnout, explore mechanisms
3	Pakistan Social and Living Standards Measurement (2015)	Survey representative at the national and district level with various development outcomes, conducted by the Pakistan Bureau of Statistics (PBS)	Analyse various mechanisms
4	Demographic and Health Survey (2017); ICF (2018)	Nationally representative survey with various development outcomes, conducted by USAID	Analyse various mechanisms

Notes: The table presents a summary of different datasets that are used for the analysis conducted in this paper. It provides a brief description of the datasets and their specific use in the analysis.

4.E Polling Station Descriptives

Table 4.E.2: Distribution of Polling Stations by Polling Location

	Number of Polling Stations	**Share**
1 Polling Station per Location	50,399	67%
2 Polling Stations per Location	11,149	15%
3+ Polling Stations per Location	14,140	19%
Total	**75,688**	**100%**

Notes: The table presents the distribution of polling stations with shared locations for the 2018 General Election conducted in Pakistan. It uses the administrative election results data at the polling station level that is used for the main analysis in this paper.

Table 4.E.3: Share of Different Types of Polling Stations by Province

Province	**Male-Only**	**Female-Only**	**Combined**	**Observations**
Balochistan	30%	25%	45%	8,338
FATA	24%	19%	57%	1,160
Federal Capital	46%	45%	9%	570
KP	34%	29%	37%	22,906
Punjab	27%	25%	48%	87,932
Sindh	22%	20%	58%	34,550
Total				**155,456**

Notes: The table presents the share of Male-Only, Female-Only and Combined polling stations in the 2018 election dataset by province. It also shows the total observations per province. The total number of observations with details about the polling station type across all provinces are 155,456. There are 1,150 observations that do not have details about the polling station type, and the total number of observations in the dataset is 156,606.

CHAPTER 5

Conclusion

This thesis studies questions of political economy and governance in the context of crime in South Asia. Chapter 2 studies the impact of upcoming elections on crime in the context of multitasking bureaucrats and politicians with re-election incentives. Chapter 3 studies the impact of criminally accused politicians on local crime. Chapter 4 studies the impact of separate-gender polling stations on voter turnout in Pakistan. All three papers combine large-scale administrative data with micro-data from surveys in order to answer questions with academic as well as policy relevance. I also undertake qualitative work to understand the mechanisms at play. Below, I discuss some of the major themes that emerge from these papers. I then elaborate on the policy implications of these results, as well as suggest some avenues for future research.

Thesis Themes

Chapters 2 and 3 of the thesis study crime, policing, and politics in the context of a developing country known for a robust electoral process and weak rule of law, and are closely related. Chapter 2 focuses on a comparison of the election period with the non-election period, whereas Chapter 3 looks within the non-election period, comparing constituencies where criminally accused politicians win narrowly against non-criminal politicians. The two papers draw on the same sets of data over the same time period and use the same categories of crime to derive the main results, which helps identify broader themes in the patterns of crime. The findings from the two papers are closely linked and consistent with each other.

In both papers, there is an overall decline in serious crimes, but for different reasons. In the case of electoral cycles, the overall decline in serious crimes is accompanied by an increase in the total number of violations, as the police more proactively prevent crime and enforce the law. On the other hand, the election of criminal politicians also reduces serious crimes, but this seems to be driven by a suppression of crime recording by the police in constituencies where a criminal is elected, as there is no difference in murders or the recording of crimes as per third-party data on political violence and domestic violence. Furthermore, there is no change in the total number of crimes in these places, indicating that change in crime only takes place on the intensive margin. These overall patterns reflect the difference in context - the timing of the election - in the two papers.

The findings from chapters 2 and 3 suggest some broader takeaways for our thinking about crime, policing, and politics in developing countries. There are three common themes that emerge: (1) the competing political incentives for increasing and reducing crime, both during the election and the non-election period, (2) the role of bureaucratic incentives and supervision mechanisms, and (3) the challenges of disentangling the roles of actual versus recorded changes in crime.

One important theme that emerges in both chapters 2 and 3 is the role of competing incentives of politicians to signal performance while also using crime to consolidate their interests. On one hand, criminally accused politicians in Chapter 3 may use their criminality as a signal to indicate that they can protect the interests of their communities (Vaishnav, 2017), and once elected, they are able to reduce crime - at the very least, recorded crime decreases. This is consistent with the 'performance story' in Chapter 2, where electoral cycles in crime may occur because politicians want to reduce crime close to elections, as this may help them project competence and get re-elected. However, as in the case of the electoral violence literature, politicians have competing impulses to use violence to consolidate their electoral gains (Chapter 2) and their rent-seeking interests (Chapter 3). This shows up in the

form of the increase in certain crimes against public order, such as riots, during the election period (Chapter 2) and the increase in own crime (Chapter 3) otherwise.[96]

A second theme concerns the incentives of bureaucrats, in this case, the police. Evidence from Chapter 2 shows that the police are much more active during the election period, as compared to the non-election period. They actively prevent crimes. Qualitative evidence suggests that they are also more active in enforcing crimes that are visible, serious, and related to the elections, and less active in enforcing other crimes, in line with what we would expect from multitasking bureaucrats (Holmstrom and Milgrom, 1991). We cannot directly observe police behaviour during the non-election period, but the evidence suggests that the suppression of crime recording taking place at this time is driven by political control over the police. In particular, the findings in Chapter 2 seem to represent a narrower subset of the findings in Chapter 3, as we are looking at a situation where political control over the police may be lower for institutional reasons, placing the focus on the behaviour of bureaucrats.

Third, a major theme that emerges from the analysis in chapters 2 and 3 is the distinction between actual and recorded changes in crime. Policing is, by its very nature, discretionary (Wilson, 1978) – it is a transaction-intensive activity that is undertaken with low levels of monitoring at the front lines, making under-recording of crimes a common occurrence across many contexts. The stylized model of the occurrence of crime, from Donohue and Levitt (2001) and Iyer et al. (2012) is valuable in outlining the distinction between the incidence and the enforcement (recording) of crime. This model can help us predict how any shock, be that the election of a criminally accused politician, or the timing of an election, can affect the occurrence and the enforcement of crime. Such a theoretically-motivated model can help us think through the findings in a structured manner. Further, in Chapter 2, I include the role of 'prevention' by the police, which is most pertinent during

[96]Whether the performance and signalling story dominates the electoral violence and rent-seeking one is beyond the scope of this thesis and could be an important area of future work.

the election period. I also rely on qualitative interviews to disentangle the role of true versus recorded changes in crime. This is possible to do in the case of the election period as it is a narrowly defined period for which no other third-party data is available. In Chapter 3, on the other hand, I use third-party data from several different sources to quantitatively analyse whether there is a change in actual, reported, and recorded crimes.

Finally, chapters 2 and 4 explore the unintended impacts of policy. In the case the election, some of the qualitative suggests that the focus on the elections reduce the effort and resources available for the enforcement of individual crimes. This can also be seen in the empirical analysis. As soon as the polling ends, there is a sharp jump in the number of serious penal-code violations, suggesting that some deferral of these serious cases was taking place around the time of polling. Chapter 4, which looks at the impact of separate-gender polling stations on female turnout, finds that not only is there a decline in female turnout in separate-gender polling stations, there is also a decline in male turnout in separate-gender polling stations. This is the case even as the objective of the policy is to increase turnout of female voters.

Overall, these themes suggest further avenues for future research, even as they contribute to our understanding of crime, policing, and law enforcement in developing countries, as well as the interactions between politicians and bureaucrats in the context of policing in this setting.

Policy Implications

The research in this thesis has implications for the work of police departments and election commissions in different countries. Chapter 2 suggests the need to improve the allocation of resources during an election period, as the under-enforcement of certain kinds of crime during the election period has welfare implications for particular groups, for example, women and children. Chapter 3 suggests the need for

distinguishing between serious and non-serious criminals in an electoral democracy, and considering strengthening the monitoring of crime recording by the police in constituencies that are criminally governed. Finally, Chapter 4 suggests the importance of better understanding the barriers to voting that women face in this context and testing policy interventions that could improve turnout for both men and women.

All the papers in this thesis rely on the use of administrative data to better understand aggregate trends, causal impact, and policy effectiveness. However, making further progress requires improved data availability, accuracy, and quality. For example, the ability to understand true changes in crime requires systematic data from crime victimization surveys. Similarly, better understanding the nature of crime and violence during elections requires information on the complaints of electoral violence received by the Election Commission, and investigations of electoral crimes by the police. Adopting a standardized approach for classifying crimes and improving data quality and comprehensiveness in police departments would go a long way in contributing to the rigorous and evidence-based study of crime and policing in developing countries.

Future Research

In terms of future research, the papers in this thesis identify several further questions that emerge from the current research. Chapter 2 provides detailed, rigorous evidence for the existence of electoral cycles in crime. Future research can help us further understand the alternative roles of bureaucrats and politicians in this setting, by examining how prevention ultimately affects political outcomes as well as changes in enforcement, thereby helping us understand whether these changes are driven by political or bureaucratic incentives. Further, in the context of crime prevention, we need to better understand the targeting and effectiveness of preventive action, as

well as whether prevention and enforcement are complements or substitutes. This has important implications for the optimal allocation of policing resources. Finally, since elections represent a composite treatment, where several political, criminal, and administrative features change simultaneously, future work could help to disentangle the role of each of these features and how they independently affect crime.

Chapter 3 provides detailed empirical evidence on the impact of criminal politicians on local crime. Future work could extend this to look at this relationship in the context of local elections, which are anecdotally understood as being more violent than state and national elections, with more severe consequences for local governance. Further, the use of the regression discontinuity design relies on close elections between criminals and non-criminals. However, the dynamics might be very different in places with less competitive elections, or in elections between non-criminals or between criminals, and future work can help us understand those contexts better. Finally, we do not know much about whether the selection of criminal politicians into office is driven by adverse selection (criminals entering politics) or moral hazard (politicians engaging in crime). This could have important implications for the mechanisms through which criminal politicians affect crime, and could be an important area for future work.

Chapter 4 provides evidence that separate-gender polling stations in Pakistan reduce turnout for both male and female voters, and shows that these results are not driven by access to resources, norms, or mobility. To further understand what may be driving these results, future research is needed to understand the constraints faced by voters. In next steps, one could undertake a survey experiment to elicit the preferences of male and female voters, and understand whose preferences the policy aligns with. Further, the implementation of the policy, in terms of queues and availability of resources in different types of polling stations is also necessary to understand.

Together, these three papers improve our understanding of crime during elections, criminal governance, and the participation of women in the electoral process, and contribute towards the literature in the fields of economics and political science. In helping us better understand the nature of crime, the incentives of politicians and bureaucrats, and the effectiveness of a voting policy, they contribute to a research agenda that aims to improve policing, governance, and policy effectiveness in the region.

References

Holmstrom, Bengt and Paul Milgrom, "Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design," *Journal of Law, Economics, & Organization*, 1991, *7* (Special Issue: [Papers from the Conference on the New Science of Organization, January 1991]), 24–52.

III, John J. Donohue and Steven D. Levitt, "The Impact of Race on Policing and Arrests," *The Journal of Law & Economics*, 2001, *44* (2), 367–394.

Iyer, Lakshmi, Anandi Mani, Prachi Mishra, and Petia Topalova, "The Power of Political Voice: Women's Political Representation and Crime in India," *American Economic Journal: Applied Economics*, 2012, *4* (4), 165–193.

Vaishnav, Milan, *When Crime Pays: Money and Muscle in Indian Politics*, New Haven: Yale University Press, 2017.

Wilson, James Q., *Varieties of Police Behavior: The Management of Law and Order in Eight Communities*, Cambridge, MA: Harvard University Press, 1978.