Descriptive representation and conflict reduction: Evidence from India's Maoist rebellion

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February 7, 2022

Abstract

Can greater inclusion in democracy for historically-disadvantaged groups reduce rebel violence? Democracy-building is a common tool in counterinsurgencies and post-conflict states, yet existing scholarship has faced obstacles in measuring the independent effect of democratic reforms. We evaluate whether quotas for Scheduled Tribes in local councils reduced rebel violence in Chhattisgarh, an Indian state featuring high-intensity Maoist insurgent activity. We employ a geographic regression discontinuity design to study the effects of quotas implemented in Chhattisgarh, finding that reservations reduced Maoist violence in the state. Exploratory analyses of mechanisms suggest that reservations reduced violence by bringing local elected officials closer to state security forces, providing a windfall of valuable information to counterinsurgents. Our study shows that institutional engineering and inclusive representative democracy, in particular, can shape the trajectory of insurgent violence.

Keywords: Counterinsurgency, Representation, India, Quotas, Democracy, Regression Discontinuity

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Introduction

Can greater inclusivity in democracy decrease insurgent violence? Research on institutional design and conflict suggests that inclusive institutions foster macro-level stability and minimize extra-systemic conflict (Acemoglu, Johnson & Robinson, 2001), and that maintaining functional democracy in diverse states requires guarantees of security and inclusion for minority groups (Dahl, 1971). Studies of conflict onset and resolution show similar results: formal protections for ethnic minorities can prevent ethnic conflict and civil wars (Horowitz, 1985), and systematically excluding minorities from power increases the risk of war (Cederman, Wimmer & Min, 2010). During war, counterinsurgents often look to democratic reforms as a way to strengthen the state and increase government ‘legitimacy’ in the eyes of civilians (Petraeus & Amos, 2006; Kalyvas, 2008). In some counterinsurgency campaigns, local democratic reforms are linked to enhanced public goods provision (Beath, Christia & Enikolopov, 2015), and improved civilian perceptions of well-being (Beath, Christia & Enikolopov, 2011; Breslawski, 2021). Recently, studies of civil war termination suggest that substantial democratic reform, even the inclusion of rebel parties in post-war elections, is associated with durable peace after even intense civil conflict (Matanock, 2017b; Joshi, Melander & Quinn, 2017).

In this article, we study a major democratic reform implemented during ongoing insurgent conflict in the Indian state of Chhattisgarh. We exploit the implementation of quotas for marginalized group representation in local councils—panchayats—and use a geographic regression discontinuity design to show that the quotas directly reduced insurgent violence, even as they were implemented during a period of intense insurgent conflict and targeted at a marginalized community constituting a key reservoir of insurgent support.

We interrogate the violence-reduction findings from Chhattisgarh with exploratory tests of

potential mechanisms, a variety of robustness checks, and a placebo test from the neighboring state of Jharkhand, which saw later implementation of identical democratic reforms amid much less intense violence. Previous research on civil war and on electoral quotas suggest two mechanisms: (1) Economic improvements — a known consequence of quotas more generally, per Pande (2003); Kadekodi, Kanbur & Rao (2008); Bardhan, Mookherjee & Parra Torrado (2010); Gulzar, Haas & Pasquale (2020) — inhibit rebels' recruitment efforts (Blattman & Annan, 2016); or, (2) improved government performance increases perceptions of state legitimacy (Chattopadhyay & Duflo, 2004). Results from additional regression discontinuity analyses show that neither explanation plausibly accounts for the full effect we observe. Qualitative evidence suggests that quotas improve the state's access to actionable information about insurgents: Maoists in Chhattisgarh responded to the reforms by assassinating holders of quota-reserved council seats on the suspicion that they provided the state with information about the Maoists. In discussing our regression discontinuity results, we posit that a change in insurgent-civilian-government information flows might account for the effect we find, and we identify areas for further research on the village-level dynamics (Balcells & Justino, 2014) that are changed by the reforms we study.

Our article makes two contributions to the vibrant literature on civil war violence dynamics, institutional reform, and conflict termination. First, because democratic reforms are almost always deployed strategically (i.e. non-randomly), previous studies have not isolated the causal effect of democratic reforms. We study a conflict where reforms were assigned non-strategically and were not part of a conflict-reduction or counterinsurgency strategy. We exploit a geographic discontinuity in the implementation of these reforms to produce a causally identified estimate of democratic reforms' effect on violence dynamics.

Second, where a substantial and theoretically-generative literature studies the effect of demo-

cratic reforms during either post-conflict peace-building or political negotiations aimed at ending the conflict (Flores & Nooruddin, 2012; Staniland, 2014; Matanock, 2017a: etc.), we examine reforms that are implemented unilaterally, *without* the backdrop of meaningful negotiation between the rebels and government.¹ We find a situation in which democratic reforms reduce violence without pre-existing buy in from all parties to the conflict. In fact, qualitative evidence suggests that the reforms change violence dynamics despite rebels never buying in. Their main response is boycotting elections and attempting to assassinate elected officials empowered by the new representation quotas. We conclude that in certain conflicts—featuring high-intensity violence with substantial rebel governance activity, organized in part around an identity cleavage, largely rural, and fought by an electoral democracy as the incumbent government—institutional engineering might reduce violence without negotiation, which existing literature assumes is a crucial condition for reforms to produce peace.

Democratic reforms and conflict

How does reforming democratic institutions reduce violence and support durable settlements to civil conflict? Literature on civil war termination and post-conflict state building suggests that creating or expanding democratic inclusion can reduce conflict by lowering the incentives to compete *outside* the system. Some research suggests that elections, for example, create credible commitment mechanisms, reducing the chance of violent contestation over political goals (Dunning, 2011; Harish & Little, 2017). Others suggest that devolution of power to local actors, a different type of reform, decreases violence in ongoing conflicts by coopting local actors (Ferwerda & Miller,

¹Matanock & Staniland (2018) note that the line between post-conflict- and during-conflict-politics is hazy given that many wars recur shortly after negotiated settlements, but they do focus on instances of meaningful rebel participation in negotiations or elections.

2014), but that decentralized power structures during war can threaten post-war stability (Daly, 2014). Other work shows that solving commitment problem is only one of the necessary steps for durable peacebuilding and reduction of violence (among many: Doyle & Sambanis, 2006; Lake, 2017).

A rich literature on negotiated settlements and peacebuilding suggests that reforms to increase inclusion and representation can support conflict resolution, if done the right way under the right circumstances. But what, if anything, does democracy reform do in wars that have not yet reached a ‘hurting stalemate’ (Zartman, 2000) that brings parties to the negotiating table? We find that targeted democratic reforms reduce insurgent violence in an ongoing war that: a) has relatively high levels of violence, b) has no meaningful negotiations, and c) is organized around an identity cleavages.

Our findings provide new, causally identified support for the broad argument that inclusion and democratization can support violence reduction in civil wars. At the same time, our findings suggest that violence reduction effects do not necessarily depend on the key belligerents investing in a negotiated settlement, an assumption or scope condition that animates much of the existing literature. Neither a ‘hearts and minds’ explanation (Petraeus & Amos, 2006; Berman, Shapiro & Felter, 2011) nor an ‘opportunity costs of fighting’ explanation (Berman et al., 2011; Dube & Vargas, 2013) likely account for the entirety of the effects we find: Full employment does not rise dramatically in the areas that see reduced violence, nor does voluntary engagement with the government through avenues like local election turnout.

In the discussion and conclusion we identify one mechanism which is consistent with our findings and may be a fertile area for future research. Quotas may work by changing the incentive structure for members of Scheduled Tribes to provide information or tips to the government. By

bringing additional members of Scheduled Tribes into elected office in high-violence, contested areas, the quotas create a new set of working relationships between the state and members of a key segment of the civilian population. The new conduit for information sharing might be particularly important given the level of quotidian interaction between civilian members of Scheduled Tribes and insurgents in many areas of Chhattisgarh (Choudhary, 2012). In line with theoretical work about information sharing during conflict (Kalyvas, 2006; Lyall, Shiraito Yuki & Imai, 2015), we suppose that Chhattisgarh's relatively intense violence is necessary for information sharing to be relevant: Where rebels have less interaction with the population and are simply less active in general, tips matter less. We present qualitative evidence that suggests local elected officials in quota areas are collaborating with the police, and are being targeted by insurgents as a result. However, we ultimately leave it to future work to tell the meso-level (Balcells & Justino, 2014) story of precisely why quotas generate the effects that we find.

Descriptive representation and quotas in India

Electoral quotas for disadvantaged groups have been a feature of Indian electoral institutions for decades, and have been studied widely in empirical social science. B.R. Ambedkar, a framer of India's constitution and a Dalit (Scheduled Caste) activist, argued that quotas for disadvantaged groups were necessary because their voices would be drowned out in majoritarian politics without increased 'weightage' compared to their demographic prevalence (Ambedkar, 1979). Since Ambedkar's initial designs, representation quotas (often called 'reservations' in India) have been expanded and challenged.

We study an electoral quota that was enacted in 1996 but implemented in different years in different states. The reform mandates reservations (quotas) for members of the historically-marginalized Scheduled Tribes (STs) in democratically-elected local government bodies. The 1996

legislation (the Panchayat (Extension to the Scheduled Areas) Act, or PESA) expanded a new system of local self-governance into ‘Scheduled Areas’—subdistricts with predominantly ST populations—that had been excluded in the original panchayat system legislation in 1992. In the new Scheduled Area panchayats, all council head positions and 50% of other seats were to be reserved for members of Scheduled Tribes. The quotas are permanent and universal in the Scheduled Areas: all local council elections must fulfill them in every election. As we describe in greater detail later, our geographic RD approach studies the effects of these reservations on insurgent violence by comparing settlements narrowly inside Scheduled Area boundaries (treated settlements) with those located just outside these boundaries (control settlements).

India’s quota and reservation systems—including quotas for other groups like women and Scheduled Castes—are widely studied as models of inclusion for disadvantaged groups (Krook & O’Brien, 2010).² Reservations shift spending priorities toward the policy interests of women (Chattopadhyay & Duflo, 2004), increase transfers to quota-targeted communities at the state (Pande, 2003) and local levels (Kadekodi, Kanbur & Rao (2008), Dunning & Nilekani (2013)), and improve credit access for targeted communities (Bardhan, Mookherjee & Parra Torrado, 2010). ST quotas in Scheduled Areas can increase ST population access to welfare programs, improve overall economic status, and improve forest conservation (Gulzar, Haas & Pasquale, 2020; Gulzar, Lal & Pasquale, 2020). Over time, electoral quotas can even reduce discrimination (Jensenius, 2017; Chauchard, 2017). We show that they can also decrease violence under certain circumstances.

²Other countries use national-level quotas to facilitate post-conflict powersharing. Unlike empirical studies of India, studies of powersharing quotas focus on polity-level stability outcomes (Cammett & Malesky, 2012; Samii, 2013).

Background: India's Scheduled Areas

The present-day Scheduled Areas have existed in some form since 1796 (with remarkably little change in the last century), when the British East India Company first established 'scheduled districts' in present-day Jharkhand in response to tribal revolts against landlords.³ Subsequent regulation under the colonial government, culminating with the *Excluded and Partially Excluded Areas Act* of 1935, established Scheduled Area boundaries that persist more or less unchanged to today. India's post-independence Constitution used the existing delineations to demarcate Scheduled Areas (SAs), and the Dhebar Commission, which formalized criteria for SA designation in 1962, left the boundaries essentially stable. Crucially for our empirical test, the Dhebar commission declined to *de-list* pre-existing Scheduled Areas that would not meet its new criteria for inclusion.

The Government of India enacted the Provisions of the Panchayats (Extension to the Scheduled Areas) Act (PESA) in 1996 to bolster self-governance for marginalized communities, including tribal groups in Scheduled Areas. In addition to decentralizing governing power, PESA required that starting in 2000 in *all* Scheduled Areas, every council chairperson and half of non-chair panchayat members—local government councilors—must come from Scheduled Tribes. State-level litigation delayed implementation of this reservation: The first reserved panchayat elections in Chhattisgarh occurred in 2005 (Paul, 2006: 3). Reserved elections were implemented simultaneously for all villages in the Scheduled Areas in January 2005, as independent reports from the central government verify (NRCDDP, Government of India, NRCDDP, Government of India: 86 & 94–95). The map of Chhattisgarh Figure 1 below shows the Scheduled Areas shaded in light red. In Appendix P, blue and pink points respectively denote villages just inside and outside the Scheduled Areas.

³'Regulation 1 of 1796'

Chhattisgarh's Scheduled Areas
(Scheduled Areas indicated by light red shading)

Figure 1. Scheduled Areas in Chhattisgarh

Background: Maoist rebellion in India

The present incarnation of India's Maoist rebellion began during the early 1980s, in regions within the present-day states of Jharkhand, Chhattisgarh, and Andhra Pradesh.⁴ Two key Maoist organizations, the Peoples War Group (PWG) and Maoist Communist Centre (MCC) merged in 2004 to form the Communist Party of India (Maoist) (Kennedy, 2014: 214). Maoist state-building has been concentrated in the Dandakaranya forest, a large region comprised of Bastar division in southern Chhattisgarh and adjoining areas in neighboring states Maharashtra and Telangana (Pandita, 2011: 54-56; Choudhary, 2012: 106-110). This region along with Scheduled Areas in Jharkhand and

⁴One institutional strategy to counter Maoists involved creating new states. In 2000, Chhattisgarh and Jharkhand were carved out of Madhya Pradesh and Bihar respectively.

Andhra Pradesh have disproportionately large populations of Scheduled Tribes which provide important reservoirs of support for the Maoists.

Maoist rebels have operated across vast swathes of India, and the government has expended substantial resources to thwart their operations and extend the state's reach in rebel-held territories. Former Prime Minister Manmohan Singh referred to the insurgency as 'the single biggest internal-security challenge ever faced by our country' (Singh, 2006), and a former Minister of Home Affairs claimed that rebels were at one point active in 223 of India's 626 districts, controlling approximately 40,000 square kilometers, roughly the size of Switzerland (Chidambaram, 2011; TOI, 2009).

The state of Chhattisgarh has a large ST population relative to other Indian states, and many ST individuals there have joined or collaborated with the Maoists (Kennedy & Purushotham, 2012; Kennedy & King, 2013; Guha, 2007). Members of STs frequently provide insurgents with information about counterinsurgent operations and withhold similar information from the government (Choudhary, 2012). Tribal communities are often caught between combatants, bearing the brunt of violence carried out by rebels, Indian security forces, and state-backed militias (Sundar, 2016). The conflict has waned in recent years, but tribal groups' central role provides compelling reasons to suppose that improvements to their representation in local democratic structures might affect insurgent violence.

Research design

We implement a geographic regression discontinuity (RD) design to estimate whether reservations for marginalized groups in local councils in Scheduled Areas reduced insurgent violence in Chhattisgarh.⁵ Our RD design compares insurgent violence in villages just inside Scheduled Areas with

⁵We focus on Chhattisgarh due to both relative conflict intensity and data availability. Naxalite insurgents have been active in the state of Andhra Pradesh, but rebel violence data for Andhra Pradesh do not exist due to extremely poor police records. Staniland & Stommes (2019) do not

villages narrowly outside Scheduled Areas. This approach relies on weaker identification assumptions than a comparison encompassing all Scheduled Areas and non-Scheduled Areas of a state; areas deep inside and far outside of Scheduled Area boundaries, in particular, are not comparable given the drastic differences in their background characteristics and potential outcomes. Furthermore, some localities far outside the Scheduled Areas are not even affected by Naxalite violence. Focusing on this relatively comparable subset of units, we estimate the effect of reservations at the boundary point. We find that quotas reduced insurgent violence in Chhattisgarh, especially so in the highest-violence areas of the state.

In formal terms, RD designs allow researchers to estimate treatment effects in settings where a unit's assignment to treatment changes discontinuously as a function of a running variable R . In our case, R_i reflects village i 's distance from the nearest Scheduled Area boundary. A treatment indicator D_i — representing whether a village is inside a Scheduled Area — is binary such that $Supp[D] \in \{0, 1\}$. Treatment assignment follows an indicator function, $D_i = \mathbb{1}\{R_i \geq c\}$, where c is a discrete cut point within the support of R_i partitioning treated and untreated units. We observe i 's treated potential outcome $Y_i(1)$ when $R_i \geq c$, and the control outcome $Y_i(0)$ when $R_i < c$. RD designs rely on the assumption that units' potential outcomes are continuous *at the cut point* in order to identify the effect of treatment at the cutoff c . We express this estimand formally:

$$\tau_{RD} = E[Y_i(1) - Y_i(0) | R_i = c].$$

Our primary approach to estimating τ_{RD} involves implementing triangular kernel-weighted, local linear regressions within narrow windows on each side of the cut point. τ_{RD} is, then, the difference between the intercepts of these two regression lines. Equation (1) expresses the functional

provide Andhra Pradesh data owing to this concern, so we are unable to include the state in our analyses. In Jharkhand, which we later use as a placebo test, violence levels have already declined prior to the implementation of treatment, such that it does not fit the scope of our hypotheses.

form of the estimator, consistent with the most modern approaches to estimating a sharp RD.⁶

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 R_i + \beta_3 D_i R_i + \epsilon \quad (1)$$

Y_i is village i 's aggregate level of Naxalite violence after the first reserved elections, and the main coefficient of interest is β_1 (the difference in violence between treatment and control units at the cut point).⁷ We also include village-level pre-treatment covariates to increase the precision of our RD estimator (Calonico et al., 2019).

We implement this estimator in the R package `rdrobust`, which selects a mean squared error (MSE) optimal bandwidth (window around the cut point), applies triangular kernel weights assigning greater weight to observations closer to the cut point, and estimates robust, bias-corrected standard errors and p-values (Calonico, Cattaneo & Titiunik, 2014b,a).⁸ The robust, bias-corrected

⁶Keele & Titiunik (2015) note that collapsing two-dimensional geographic distance into a one-dimension forcing variable (distance from the border) may be problematic when units are quite geographically distant from each other, despite having similar one-dimensional running variable values. We relax this potentially-problematic assumption in two ways: (1) Appendix F re-estimates our main specification incorporating, separately, units' latitude and longitudes within a geographic polynomial term. (2) Appendix G implements the one dimensional running variable approach on control/treatment units in relatively compact sub-regions, such that units with similar running variable scores will be closer to each other than in the full sample approach. The findings are consistent with our main estimates. See Mattingly (2017) and Rozenas, Schutte & Zhukov (2017) for applied examples of these approaches.

⁷In Appendix F, we estimate treatment effects using a higher-order polynomial functional form, consistent with Dell (2010). The results are consistent with Table I. Gelman & Imbens (2019) caution against using higher order polynomial estimators for RD estimation because the estimates are typically quite noisy and sensitive to the order of polynomial selected; therefore we use the estimator in Equation (1) for our main results.

⁸Importantly, `rdrobust` pre-specifies the bandwidth selection procedure and effect estimator, constraining the potential for p-hacking through researcher degrees of freedom.

errors estimated by `rdrobust` tend to be sufficiently conservative because they mitigate the poor small-sample properties of the typical linear regression standard error estimators. In Appendix D, we re-estimate τ_{RD} with similarly conservative Conley (1999) standard errors to account for spatial auto-correlation; the results are quite similar.

We define the outcome variable in two ways. The first involves using $Y_{i,total}$ as the outcome variable, representing the total number fatalities in village i from the year the state implemented reservations until 2014 (ten years in Chhattisgarh). Second, we define the outcome variable as $Y_{i,t}$, the total number of fatalities in village i for $t = 1, 2, 3$, etc. year spans after the implementation of reservations. This allows us to examine the effects over time. Ultimately, the results are consistent for both approaches.

RD identification assumptions

The RD design relies on the assumption of the continuity in potential outcomes at the cutpoint. We evaluate the assumption empirically through multiple approaches. First, we present qualitative evidence regarding the creation of the Scheduled Area boundaries. The historical record suggests that the precise location of the boundaries were typically chosen without reference to the characteristics of villages. Second, we assess pre-treatment covariate balance by evaluating whether Indian census data from 2001 substantially differs across treatment and control groups. While this evidence supports our main identification assumptions, we conclude by outlining supplemental RD estimation strategies which complement our main approach.

Creating the Scheduled Area boundaries

The manner in which the Scheduled Area boundaries were drawn is crucial for assessing the comparability of treatment and control settlements. When the British Raj formalized the Scheduled Areas in 1935, colonial administration had extremely poor information about the demographic composi-

tion of rural regions, drawn from an administrative census conducted in 1931. As an official report indicates, the Census project in rural areas was comically under-staffed, with individual enumerators in rural regions covering, on average, between 836 and 1,460 square miles (Hutton, 1933: ix). The existence of multi-lingual populations and tribal groups—particularly in the Central Provinces (which includes present-day Chhattisgarh)—further complicated recording whether a settlement was associated with a particular tribal group (Hutton, 1933: 352-353). British Indian colonial censuses in the 19th and 20th centuries also relied on local notables to provide details about local characteristics in areas where they had difficulties collecting information. Data from key informants was likely biased as residents of rural localities sought to avoid the census due to fears of taxation (Jiwani, 2020 citing Waterfield, 1875). In detailed lists of groups designated as ‘tribes’ in the 1931 Census, the omission of numerous tribal groups indicates that the list was haphazard and far from complete (Hutton, 1933: 462-468). Overall, evidence suggests that British demarcation of Scheduled Area boundaries was based on extremely coarse knowledge of local demographic characteristics. It is quite likely that settlements very close to the boundary on either side were similar in their baseline characteristics.

Covariate balance

We quantitatively evaluate the reliability of the continuity assumption by testing for pre-treatment covariate imbalance at the cut point. As results in Appendix B show, none of the pre-treatment covariates exhibit any imbalance for Chhattisgarh. This quantitative evidence, along with the qualitative historical evidence presented in the prior section suggest that settlements narrowly inside an outside the Scheduled Area boundaries constitute comparable units for assessing the effect of reservations on insurgent violence.

Data

Our RD analysis relies primarily on three sources of data. First, the Socioeconomic Data and Applications Center (SEDAC) repository provides village-level geospatial and socioeconomic data for 1991 and 2001 in Chhattisgarh (Meiyappan et al., 2018). These data include coordinates for all villages and dozens of socioeconomic indicators collected in the Indian census. The geospatial information allows us to measure the distance from each unit to the nearest Scheduled Area boundary, and the socioeconomic data allowed us to assess pre-treatment covariate balance and achieve precision gains in our RD estimation.

We measure insurgent violence at the village-level in Chhattisgarh with a dataset containing granular information about Indian security force fatalities in internal conflicts (Staniland & Stommes, 2019). Drawing on publicly-available booklets from the Ministry of Home Affairs's Border Security Force (BSF), Central Reserve Police Force (CRPF), and state-level police sources, this fatality-level dataset contains details about each service member killed in domestic security operations (Ministry of Home Affairs (Government of India), 2015a,b). The state police data play a crucial role in our analysis, as these organizations have been heavily-involved in operations against Naxalites. As noted earlier, we are unable to include high-intensity regions of Andhra Pradesh in our analysis due to the absence of police fatalities data from that state. Central armed forces and state-level police forces have strong incentives to commemorate their service members killed in action and invested substantial resources in compiling and publishing this information, bolstering our confidence that the data are a comprehensive measure of security force fatalities (Staniland & Stommes, 2019). Furthermore, supplemental results in Appendix A show that security force fatalities are highly correlated with civilian casualties such that the granular security force data used here are appropriate proxies of overall insurgent violence.

Some fatality entries in the Staniland & Stommes (2019) dataset do not indicate the location at the village-level despite listing the state, district, and date of death. We recovered missing village locations from archives of leading English-language daily newspapers in India, *The Times of India*, *Hindustan Times*, and *The Indian Express*. We further supplemented those fatality entries with missing geographic coordinates using the Google Maps API and the ‘India Place Finder’ tool (Mizushima Lab at University of Tokyo, 2019). We then coordinate-matched each fatality with the corresponding settlement in Indian Census shape files from SEDAC. The resulting settlement-level datasets for Chhattisgarh and low-violence Jharkhand (analyzed later as a placebo test) include socioeconomic indicators along with the annual number of security force fatalities from 2000 to 2014. To reiterate, for our RD analyses, we tabulate security force fatality totals for each village, creating a count variable at the village level which corresponds to the level/unit at which treatment (ST reservations) is assigned.

Several characteristics of the fatality data, for which Maoists were perpetrators, are noteworthy. First, 1,043 security force fatalities occurred in Chhattisgarh between 2000 and 2014.⁹ Second, Figure 2 illustrates spatial variation in Maoist violence in Chhattisgarh. The violence was heavily concentrated in the South: Dantewada in southern Chhattisgarh, for instance, surpassed all other districts in the state with 445 security force fatalities from 2000 to 2014.

The security force fatality data used in our analysis reflect overall levels of insurgent violence. In Appendix A, we show a positive and statistically significant correlation between civilian and security force fatalities aggregated to the district level in Chhattisgarh by using a district-level dataset of each fatality type constructed through local press sources (Dasgupta, Gawande & Kapur, 2017). These estimates suggest that the fatality data used in our analyses reliably reflect overall

⁹For context, American fatalities in the entire country of Afghanistan from 2001-2014 number around 2,200.

Security Force Fatalities in Chhattisgarh by District (2000-2014)

Figure 2. Spatial variation of Maoist violence in Chhattisgarh

rebel violence.

The final source of evidence upon which our RD analyses rely are detailed lists from the Indian Government's Ministry of Panchayati Raj which identify the precise location of Scheduled Areas (Ministry of Panchayati Raj (Government of India), Ministry of Panchayati Raj (Government of India)). States usually identify Scheduled Areas with a list of sub-districts, though some states list localities within subdistricts. Following Gulzar, Haas & Pasquale (2020), we consider an entire subdistrict to be part of the Scheduled Area if any portion of the subdistrict is listed as such. We incorporated this information into a shape file of all subdistricts in Chhattisgarh, marking those within which settlements are classified as Scheduled Area units (ML InfoMap (Firm), 2006). We then combined that shape file with village-level coordinates to construct our running variable – i.e. an estimate of each settlement's distance from the nearest Scheduled Area boundary.

Results

Geographic RD estimates and robustness checks show that reservations in panchayat elections reduced insurgent violence in Chhattisgarh. Tests across a battery of pre-treatment indicators show balance across treatment and control villages in the state. The point estimates presented below are

consistent across multiple specifications and numerous robustness checks we include in appendices.

Main RD estimates

We first estimate the geographic RD for Chhattisgarh using $Y_{i,total}$ as our outcome variable — i.e. the total number of fatalities in village i after the first reserved elections in 2005, through 2014. The statistically significant results in Table I show that during the period after Chhattisgarh’s first elections (2005-2014), less insurgent violence occurred in Scheduled Area villages than in those without reservations. The village-level effect on violence in Chhattisgarh is equivalent to 15 fewer fatalities at the subdistrict-level (a unit comparable to a county in the United States) and approximately 89 fewer fatalities at the district-level. We present additional results in Appendix D which indicate that these estimates hold when using Conley standard errors to account for spatial autocorrelation.

Table I. Main RD results: Reserved election effects on insurgent violence
Outcome variable: Total fatalities after first reserved elections until 2014

Chhattisgarh (2005-14)						
Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
-0.071	[-0.131, -0.011]	0.021	20,204	6,597	23.29km	Yes
-0.059	[-0.119, 0.001]	0.056	20,204	6,713	23.72km	No

The covariate-adjusted RD estimates include the following pre-treatment, village-level characteristics: total population, Scheduled Tribe population, Scheduled Caste population, number of literate residents, male population, primary school indicator, middle school indicator, presence of community social facilities, ‘main work’ population, ‘total work’ population, cultivator population, paved road indicator, mud road indicator, domestic-use electricity availability indicator, medical facility indicator, well water indicator, bank facility indicator.

Over-time RD estimates

To further explore the over-time changes in treatment effects, Figure 3 plots the rdrobust point estimates and confidence intervals associated with different periods of time after the initial introduction of quotas in the state.¹⁰ The results indicate that reservations reduced violence in Chhattisgarh within two to four years after the first reserved elections and that the effect persists (and grows)

¹⁰The corresponding estimates for this plot can be found in Appendix E.

thereafter.

Figure 3. Comparing RD effects over time for Chhattisgarh

All point estimates and robust, bias-corrected 95% confidence intervals are derived using `rdrobust`. The results indicate that reservations initially reduced insurgent violence in Chhattisgarh within three years of their implementation—the confidence interval for Chhattisgarh at three years excludes zero.

Robustness checks

While the historical record and balance tests suggest that the Scheduled Area boundaries in Chhattisgarh were orthogonal to nearby villages’ characteristics, three robustness checks focus on subsamples where this assumption is even more defensible. First, we examine the Scheduled Area boundaries and whether they coincide with topographical characteristics and colonial infrastructure (i.e. railways), and then exclude in additional RD analyses any subdistricts featuring topographical features which are potentially discontinuous at the Scheduled Area boundary (see Appendix G). Second, we estimate RD treatment effects in regions with particularly rugged terrain in Chhattisgarh (see Appendix H), because given the relatively rough terrain and the absence of a legible colonial-era local population, it is even likelier that the precise placement of Scheduled Area boundaries in these regions was made without respect to local characteristics. The results from these robustness checks are consistent with the main results we presented above.

Other robustness checks are included in Appendix C which presents RD results for alterna-

tive bandwidths, and Appendix D implements a local linear RD estimator with Conley standard errors accounting for spatial auto-correlation (Conley, 1999). Following Dell (2010), we also estimate effects with a higher-order polynomial regression specification that includes a flexible smooth function along latitude and longitude (see Appendix F). We estimate the RD effect using various ‘placebo’ cut points (Appendix K), and censored bandwidths which attempt to account for potential spillovers (Appendix J). Finally, we present results from difference-in-differences estimators in Appendix L. Across all robustness checks, the results align with main RD estimates, supporting our conclusion that reservations reduced violence in Chhattisgarh.

Evaluating results in Chhattisgarh: a block jackknife sampling approach

To understand which areas of Chhattisgarh drive the violence reduction effects, we re-estimate the main RD specification in a block jackknife routine, estimating τ_{RD} separately *holding out* each individual sub-district. Results in Appendix Q show that five sub-districts are individually necessary for a significant main result: Consistent with our theoretical expectations about reservations’ violence-reducing effects, we find that the highest violence sub-districts in Chhattisgarh (in Dantewada and Bastar) drive our main result.

Placebo Test: Lower-Violence Jharkhand

The RD estimates from Chhattisgarh indicated that reservations for ST communities in local councils subsequently reduced insurgent violence in high-intensity conflict settings. Next, we conducted a placebo test to discern whether the same type of reservations reduced insurgent attacks in Jharkhand, a neighboring state where the Maoist insurgency was much weaker and violence occurred with much less frequency than in Chhattisgarh. Ethnographic research on Maoist insurgents in Jharkhand illustrates that rebel organizations in the state are fragmented and possess a relatively limited capacity to carry out attacks (Shah, 2006). The security force fatality data from Staniland

& Stommes (2019) reinforce this qualitative claim; 436 Jharkhand police and central security force fatalities resulted from insurgent violence from 2000 to 2014, less than half of the total security force deaths in Chhattisgarh during the same time period, and in a larger state.

We analyzed the affect of quotas on insurgent violence in Jharkhand using the same RD estimator implemented on our Chhattisgarh data. Table II presents the main RD estimates for this placebo analysis. Note that the estimator for Jharkhand which includes covariates for precision gains simultaneously adjusts for any imbalanced characteristics.¹¹ Precisely-estimated null effects in Jharkhand across numerous specifications and robustness checks (see Appendices C, E, F, L) indicate that the introduction of ST quotas did not affect subsequent insurgent violence in the state after implementation in 2010. This test, which shows a precisely estimated null effect, supports our claim that the efficacy of reservations may be confined to high-violence settings.

Table II. Placebo RD results: Reserved election effects on insurgent violence
Outcome variable: Total fatalities after first reserved elections until 2014

Jharkhand (2010-14)						
Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
0.001	[-0.007, 0.009]	0.780	32,927	15,585	22.27km	Yes
0.001	[-0.007, 0.008]	0.86	32,927	13,696	18.19km	No

The covariate-adjusted RD estimates include the following pre-treatment, village-level characteristics: total population, Scheduled Tribe population, Scheduled Caste population, number of literate residents, male population, primary school indicator, middle school indicator, presence of community social facilities, ‘main work’ population, ‘total work’ population, cultivator population, paved road indicator, mud road indicator, domestic-use electricity availability indicator, medical facility indicator, well water indicator, bank facility indicator.

¹¹We include covariate balance checks for Jharkhand in Appendix B. One robustness check for Jharkhand in Appendix I entails restoring covariate balance by removing a district-level block of villages whose presence induces the imbalance. The RD estimates in this robustness check for Jharkhand are null as well.

Discussion: Explaining the reduction of violence in Chhattisgarh

What explains *how* quotas reduced violence in Chhattisgarh? Qualitative evidence suggests that panchayat reservations coopted (or functionally coerced) key members of Scheduled Tribes into closer collaboration with Indian state security forces, creating an information windfall for counterinsurgents. This boon to security forces is consistent with a subsequent advantage in undermining the insurgents' operations. In contrast, we find weaker support for alternative explanations which center on improvements to the Indian state's legitimacy in Scheduled Areas and the economic welfare of residents living in Scheduled Areas. Future research and data collection efforts will be necessary to more rigorously disentangle potential mechanisms.

Political economy of information

The introduction of reservations in Scheduled Area panchayats brought the Indian state (police officials, in particular) into closer contact with local elected members from ST communities. After Chhattisgarh's first reserved panchayat elections, Naxalites began targeting *sarpanches* (council heads) and other panchayat officials who they accused of collaborating with security forces. Press reports, NGO investigations, and ethnographic studies illustrate the nexus between counterinsurgents and local ST officials, providing evidence—albeit indirect—for why Naxalites started targeting panchayat officials and for the later reduction in insurgent violence. Consider a concrete example of local elected officials entering the counterinsurgents' orbit:

‘Bir Sai Ghawde of Teregaon bought himself a cell-phone when he won the gram-panchayat elections in February [2010]. “The Maoists killed him and took away the cell-phone and our landline,” said his widow Sanarubai, “He was the Sarpanch; so he often met the police on official work.” The police claims to cultivate only those willing to risk being informers’ (Sethi, 2010).

Panchayat officials in Naxalite-affected areas were often willing to put themselves at great per-

sonal risk by collaborating with security forces, even when counterinsurgency organizations do not provide extensive security for those elected officials (Iqbal, 2016). This collaboration did not go unnoticed by the insurgents who, according to Sundar (2018), ‘have argued that elections for the post of sarpanch [head of the local council]...are undesirable since individuals are easily corruptible and then function as agents of the state’ (Sundar, 2018: 89).

Information from civilians is a valuable resource for opposing sides in a civil war; shifts in the provision of this commodity have critical implications for conflict outcomes and territorial control. Journalists working in the Dandakaranya region of Chhattisgarh note how Maoists targeted sarpanches and other panchayat officials because they provided information to the police and served as a conduit between ordinary citizens and the Indian state.¹² Residents in this region of Chhattisgarh noted that prior to the January 2005 introduction of reserved panchayat elections, the Naxalites typically refrained from targeting notables from ST communities (HRW, 2008: 22). Reports from after 2005 illustrate the clear shift in Naxalite targeting: rebels singled out elected members of STs who were perceived as collaborators. Consider one example:

‘On 12 August 2005, alleged Maoists killed a village Sarpanch, Rajman Uike of village Baghdadongari after he was kidnapped along with three others. His body was recovered on Narayanpur road with his hands and legs tied. The Maoists reportedly claimed that the Sarpanch was ‘convicted to death’ in their Jan Adalat [People’s Court] on charges of being a police informer’ (ACHR, 2006: 31).

In the years since, Naxalites have repeatedly killed tribal sarpanches inside Scheduled Areas (e.g. PTI (2013, 2017, 2019); Hardikar (2013)). In each case, Naxalites accused the panchayat official of being a security force informant, and we suspect that these accusations were often accurate, given the aforementioned nexus between counterinsurgents and ST panchayat officials. The documented shift in information provision in the years from 2005 onward (elections occurred in January 2005),

¹² Author’s personal communication, New Delhi, March 2020.

along with existing research showing how improved access to information gives counterinsurgents a relative advantage vis-à-vis rebel groups, tentatively support our information theory.

Why might introducing panchayat reservations change the political economy of information in Scheduled Areas when ST quotas for state and national legislatures have already been in force for over half a century? We posit that there are three critical features of the panchayat quotas (compared to state legislature quotas) that might drive changes in information provision. First, panchayat members unlike higher-level legislators play important roles in the day-to-day implementation of public services, and have routine, un-mediated interactions with their constituents (Bussell, 2019: 144). This routine interaction means that panchayat members likely come across the valuable counterinsurgency information described above in the course of their regular duties. Second, panchayat members—unable to credibly disavow the state by virtue of their participation in a local government body—are uniquely vulnerable compared to their legislators. Panchayat members, unlike MLAs, do not have the luxury of residing outside the villages they represent, living beyond the reach of rebel groups in district towns or the state capital. Further, because panchayats have no supervisory authority over local or state bureaucrats (Again see Bussell, 2019: 144), they have no *de jure* power to order up protection from state security services. In this situation, we posit the best way for a panchayat member to receive security from rebel assassination is to strike a security-for-information bargain with the security services operating in their area.

Finally, one possible explanation for the effect we find is that panchayat quotas are an unusually *intense* intervention in terms of ST legislative representation. National- and state-level quotas reserve individual constituencies. Chhattisgarh's state-level quotas, which are the highest in India's 14 major states, reserve only 32% of seats for STs compared to 50% plus the council presidency for panchayat reservations.

Alternative explanations: State legitimacy and the opportunity costs of rebellion

Previous counterinsurgency literature implies that reservations could erode rebel support either by enhancing the state's legitimacy vis-à-vis marginalized groups, or by improving marginalized community members' socioeconomic conditions, thereby increasing the opportunity costs of joining a rebellion. These alternative explanations for our finding in Chhattisgarh do not exhaust the universe of potential mechanisms, but we focus on them given their relative prominence in the literature. We find limited support for these explanations compared to the information provision mechanism.

First, we evaluate whether ST reservations improved state legitimacy in Scheduled Areas with an additional geographic RD specification using voter turnout as the outcome variable. If the state's legitimacy increased in Scheduled Areas, then we might expect participation in 'official' political processes to be higher than in nearby non-Scheduled Areas. We measure this outcome with booth-level vote totals for Chhattisgarh's 2018 state election, scraped from official Form 20 documents. Booths are the smallest geographic unit for which votes are tabulated and often correspond to individual villages. Merging booth-level vote totals with a shape file containing coordinates for all booths in Chhattisgarh (Susewind, 2014), we measure the distance of each booth to the nearest Scheduled Area boundary. RD results presented in Appendix N suggest that reservations had no effect on votes cast in Scheduled Areas versus non-Scheduled Areas. If anything, the negative (though not statistically significant) estimated treatment effect indicates lower levels of voting in Scheduled Areas.

Alternatively, ST reservations might diminish rebel violence by improving marginalized individuals' economic prospects, thereby increasing the opportunity cost of taking up arms against the state. We indirectly test this hypothesis in Chhattisgarh with another geographic RD analysis which uses settlement-wise male employment rate as the outcome. Using Indian census data from

2011, we measure each settlement's rate of gainful employment for men by dividing its 'male main work population' (number of male residents employed for at least six months in the previous year) by the 'total male work population' (total number of working-age male residents). Results presented in detail in Appendix [O](#) indicate that ST reservations did not have a positive, statistically significant effect on this measure of male employment.

Of course, there may be measures of state legitimacy beyond voting behavior, like survey indicators from Chhattisgarh, which would more cleanly test the 'hearts and minds' theory. Second, there may be a specific subset of men within the working-age male population who would be considered the most 'at-risk' to take up arms against the state and for whom employment rates would be most important to study. Ultimately, either the economic or legitimacy mechanisms might be at work in tandem with the political economy of information mechanism for which we *do* find support, but preliminary probes into why quotas measure reduced violence in Chhattisgarh support a political economy of information theory.

Conclusion

Our findings build on civil war research in multiple ways. First, in a new, causally identified test, we find support for the widely-studied idea that democratic reforms can ameliorate conflict and reduce violence in high-intensity regions in civil wars. Second, we extend previous literature, which mostly focuses on the context of negotiated settlements and post-war powersharing. Our findings show that ongoing negotiations—i.e. attempts to agree to a ceasefire, or to reach a broader political settlement to the conflict—are not strictly necessary for democratic reforms to reduce violence. On the contrary, more intense conflict to start with might be a necessary condition for reforms to decrease violence: our 'placebo' test in low-violence Jharkhand suggests that reforms in less-intense conflict have no effect on violence levels.

The Government of India also uses reservations for Scheduled Tribes, Scheduled Castes, and women in national and state legislative assemblies. These reservations might also have affected insurgent violence during the long history of the Naxal conflict. Though our research design does not allow us to draw conclusions about the effects of representation in higher levels of government, we see these other reservations as natural area for future research. We focus this project on panchayat-level reservations due to the panchayat's hyper-local orientation. Civilians and rebels typically interact with the state at local levels, not the assembly in a state capital or the parliament in Delhi. The quotas we study in village-level institutions constitute a substantial policy change to the arms of the state with which civilians and rebels most frequently interact.

Further, our investigation into the mechanisms that explain the effect of democratic reforms in Chhattisgarh highlight important lessons for counterinsurgents and state builders. Counterinsurgents have long held that focusing on the 'hearts and minds' of civilians can generate collaboration with the state and produce a windfall of intelligence. In recent decades, counterinsurgency practitioners used institutional reforms to win hearts and minds in conflicts like the war in Afghanistan. We find that certain democracy-enhancing reforms can depress violence levels, but not necessarily by winning hearts and minds in large numbers. While improving the legitimacy of the state may be a desirable long-term goal for state builders, the case of Chhattisgarh suggests it may not be critical for short-term violence reduction. Nor do we find evidence that building legitimacy is more feasible than recent, pessimistic studies suggest (Jackson, 2014). Democratic reforms can meaningfully shape conflict through pathways other than popular opinion and allegiance.

We hope that this study prompts more research on local meso-level puzzles of civil conflict, particularly more investigation into the mechanisms that link local institutions to violence dynamics. We wonder, for example, since reservations do not seem to motivate more participation in state

functions, would other policies like measures focused on electoral integrity potentially have such an effect? We also suggest that future research could dig within our village-level findings to more precisely measure and richly theorize the factors that influence the behavior of local elites in civil wars.

Replication data statement

Replication data: The dataset, codebook, and R script files for the empirical analysis in this article, along with the online appendix, can be found at <http://www.prio.org/jpr/datasets>. All analyses were conducted in R.

Acknowledgements

We are grateful to P.M. Aronow, Erica Chenoweth, Fotini Christia, Andrew Halterman, Elizabeth Nugent, Rohini Pande, Roger Petersen, Fredrik Sävje, Steven Wilkinson, and Elisabeth Wood for insightful comments on previous drafts of this article. We also thank many anonymous reviewers and the JPR editorial team. Finally, we thank audiences at the Harvard-MIT-Tufts-Yale Political Violence Conference (2020), MIT Security Studies Working Group (2019), Yale Middle East and North African (MENA) Politics Working Group (2020), the Yale University Comparative Politics Workshop (2020), and the Empirical Studies of Conflict Project Annual Meeting (2021).

Funding

Milliff gratefully acknowledges support from a U.S. Institute of Peace-Minerva Peace & Security Scholar Award. The views expressed here are those of the authors, and do not necessarily reflect the views of the U.S. Institute of Peace, the Minerva Research Initiative, or the Department of Defense.

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Online Appendices: Descriptive Representation and Conflict Reduction

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A Relationship between civilian and security force fatalities

One potential concern with our fatality data is that it is strictly measuring insurgent violence against security forces rather than measuring insurgent violence more broadly—i.e., against security forces *and* civilians. No data are publicly available which allow us to construct a measure of village-level civilian fatalities. However, an existing study’s publicly-available dataset provides district-level measures for security force and civilian fatalities in Chhattisgarh (Dasgupta, Gawande & Kapur, 2017). So, we regressed security force fatalities on civilian fatalities and find a strong, statistically significant correlation between the two (see Table 2).

Table III. Correlation between security force and civilian fatalities in Chhattisgarh

Outcome variable: security force fatalities			
Predictor	Estimate	95% CI	P-Value
Civilian Casualties	0.329	[0.165, 0.492]	0.00

The strong correlation between these two variables improves our confidence that our data regarding security force fatalities in Chhattisgarh are a good proxy for overall patterns of insurgent violence.

We also evaluate whether the number of insurgent attacks against security forces, in general, corresponds with security force fatalities. Specifically, we use the UCDP Georeferenced Event Dataset (GED) Global version 21.1 (Pettersson & Öberg, 2021; Sundberg & Melander, 2013).

The GED dataset covers individual events of organized violence across the globe and encompasses the conflict in Chhattisgarh that we study (2005-2014). Examining the GED data from Chhattisgarh, we regress the total number of incidents for each year where security forces on the number of security forces killed each year. This regression allows us to determine whether an individual year with relatively few attacks produced a disproportionately large number of fatalities. As our results in Table IV demonstrates, this is *not* the case: the correlation between these two indicators is positive statistically significant, suggesting that overall attacks (which often involve lethal *and* non-lethal violence) correspond quite closely with the number of fatalities.

Table IV. Analysis GED data in Chhattisgarh (2005–2014): total attacks vs. total security force fatalities

All estimates include HC2 robust standard errors					
		point estimate	std. error	p-value	outcome
1	(Intercept)	25.42	10.03	0.03	events
2	casualties	0.23	0.08	0.02	events

B Balance Tests

We estimate whether treatment and control units are similar on a broad range of pre-treatment characteristics. Using 2001 Indian census data for each of our observations within the bandwidth in our main results, we find that we achieve balance on a battery of covariates. To account for the imbalance in some characteristics in Jharkhand, we included them as covariates the main RD estimates reported. Ultimately, this balance test assesses whether treatment status “predicts” pre-treatment covariate values. Tables 3 and 4 present these results for Chhattisgarh and Jharkhand, respectively.

Table V. Balance Test: Chhattisgarh

Pre-Treatment Covariate	Estimate	95% CI	P-Value
ST Population	64.05	[-60.51, 188.60]	0.314
Total Population	262.08	[-210.32, 734.48]	0.277
SC Population	12.59	[-47.51, 72.70]	0.681
Literacy	160.521	[-126.02, 447.06]	0.272
Male Population	129.504	[-106.76, 365.77]	0.283
Primary Schools	0.053	[-0.043, 0.149]	0.281
Paved Rds.	0.036	[-0.026, 0.099]	0.257
Power Supply	-0.004	[-0.063, 0.054]	0.884

Table VI. Balance Test: Jharkhand

Pre-Treatment Covariate	Estimate	95% CI	P-Value
ST Population	70.77	[31.18, 110.36]	0.000
Total Population	101.86	[-72.95, 276.67]	0.253
SC Population	18.90	[0.234, 37.567]	0.047
Literacy	35.07	[-86.092, 156.229]	0.571
Male Population	52.43	[-40.838, 145.703]	0.271
Primary Schools	0.105	[0.053, 0.157]	0.00
Paved Rds.	0.144	[0.086, 0.201]	0.00
Power Supply	0.143	[0.087, 0.199]	0.00

C RD Estimates Using Alternative Bandwidths

We also test whether our RD estimates in Chhattisgarh and Jharkhand are robust to alternative bandwidths. The robustness checks for Chhattisgarh and Jharkhand are reported in Tables 5 and 6, respectively. Our point estimates remain quite stable over a wide range of bandwidths narrower and wider than the MSE optimal ones used for our main estimates in Chhattisgarh and Jharkhand. Due to the small unit-level effect size we are trying to detect, the bandwidths narrower than the MSE-optimal one provide a sample which is insufficiently large to clear traditional thresholds of statistical significance, but our confidence in the effects estimated as part of our main results are reinforced due to the consistency in the sign of the treatment coefficient.

Table VII. Reserved Election Effects on Insurgent Violence (Chhattisgarh)
Alternative Bandwidths

Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
-0.069	[-0.127, -0.011]	0.019	20,204	8,201	30km	Yes
-0.040	[-0.094, 0.013]	0.137	20,204	5,809	20km	Yes
-0.047	[-0.142, 0.048]	0.335	20,204	1,768	5km	Yes
-0.123	[-0.339, 0.094]	0.267	20,204	410	1km	Yes

Table VIII. Reserved Election Effects on Insurgent Violence (Jharkhand)
Alternative Bandwidths

Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
0.001	[-0.007, 0.008]	0.861	32,927	18,783	30km	Yes
0.003	[-0.001, 0.007]	0.155	32,927	14,598	20km	Yes
0.005	[-0.004, 0.013]	0.287	32,927	4,581	5km	Yes
0.00	[0.00, 0.00]	NA	32,927	972	1km	Yes

D RD Estimates using Conley Standard Errors

Conley (1999) devises a procedure for estimating standard errors in the presence of spatial autocorrelation between units. To complement our `rdrobust` estimates in the main body of the paper, we alternatively conduct inference for our RD treatment effect estimates by estimating Conley standard errors. We do so using the default functional form in `rdrobust` and within two different bandwidths. We first use the MSE-optimal bandwidth selected by `rdrobust` and then implement our RD estimator within a bandwidth three fourths the size of the MSE-optimal one for under-smoothing purposes because our treatment effect estimator in this particular implementation does not incorporate a bias correction. Ultimately, the results using Conley standard errors in Table IX are consistent with those in the main body of the paper.

Table IX. RD Results Using Conley Standard Errors: Reserved Election Effects on Insurgent Violence

Outcome Variable: Total Fatalities After First Reserved Elections Until 2014

Chhattisgarh (2005-14)						
Estimate	Conley Std. Error	Two-tailed P-Value	Total Units	Units Inside BW	BW	Covs.
-0.0627	0.031	0.042	20,204	6,597	23.29km	Yes
-0.0589	0.030	0.056	20,204	5,230	17.47km	Yes
Jharkhand (2010-14)						
Estimate	Conley Std. Error	Two-tailed P-Value	Total Units	Units Inside BW	BW	Covs.
0.001	0.004	0.753	32,927	15,585	22.27km	Yes
0.002	0.006	0.744	32,927	12,848	16.70km	Yes

These estimators include the following pre-treatment, village-level characteristics: total population, Scheduled Tribe population, Scheduled Caste population, number of literate residents, male population, primary school indicator, middle school indicator, presence of community social facilities, “main work” population, “total work” population, cultivator population, paved road indicator, mud road indicator, domestic-use electricity availability indicator, medical facility indicator, well water indicator, bank facility indicator.

E Over-Time RD Estimates

“CCT BW” refers to the MSE-optimal bandwidth selected by `rdrobust`.

Table X. Over-time RD Results: Reserved Election Effects on Insurgent Violence

Outcome Variable: Total Fatalities

Chhattisgarh							
Yrs. after First Reserved Elects.	Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	CCT BW	Covs.
1	-0.000	[-0.000, 0.000]	0.174	20,204	1,747	4.90km	Yes
2	-0.004	[-0.013, 0.006]	0.439	20,204	5,360	18.01km	Yes
3	-0.022	[-0.042, -0.001]	0.040	20,204	5,943	20.52km	Yes
4	-0.028	[-0.063, 0.008]	0.124	20,204	6,158	21.44km	Yes
5	-0.033	[-0.070, 0.003]	0.076	20,204	6,177	21.51km	Yes
6	-0.059	[-0.114, -0.004]	0.035	20,204	6,593	23.25km	Yes
7	-0.069	[-0.126, -0.012]	0.018	20,204	6,356	22.23km	Yes
8	-0.068	[-0.125, -0.010]	0.021	20,204	6,304	22.01km	Yes
9	-0.067	[-0.125, -0.008]	0.025	20,204	6,456	22.69km	Yes
10	-0.071	[-0.131, -0.011]	0.021	20,204	6,597	23.29km	Yes
Jharkhand							
Yrs. after First Reserved Elects.	Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	CCT BW	Covs.
1	0.004	[-0.003, 0.010]	0.256	32,927	12,778	16.55km	Yes
2	0.001	[-0.006, 0.008]	0.749	32,927	13,556	17.91km	Yes
3	0.002	[-0.004, 0.008]	0.446	32,927	11,466	14.41km	Yes
4	0.001	[-0.007, 0.009]	0.780	32,927	15,585	22.27km	Yes

The covariate-adjusted RD estimates include the following pre-treatment, village-level characteristics: total population, Scheduled Tribe population, Scheduled Caste population, number of literate residents, male population, primary school indicator, middle school indicator, presence of community social facilities, “main work” population, “total work” population, cultivator population, paved road indicator, mud road indicator, domestic-use electricity availability indicator, medical facility indicator, well water indicator, bank facility indicator.

F RD Estimates Using Higher-Order Polynomial Fits

An alternative approach to estimating treatment effects in geographic RD settings entails fitting higher-order polynomial fits that include a flexible smooth functions along two dimensions, latitude and longitude (Dell, 2010). The functional form for latitude and longitude in this regression takes the following specification: $x + y + x^2 + y^2 + xy + x^3 + y^3 + x^2y + xy^2$, where x is the latitude and y is the longitude of the unit. We fit this estimator within the MSE-optimal bandwidth selected by `rdrobust` as well as three fourths the value of the MSE-optimal bandwidth for undersmoothing purposes. Along with this higher order smooth function, we include a battery of pre-treatment covariates. The results in Table XI are consistent with the main results reported in the paper indicating that reservations reduced violence in Chhattisgarh but not Jharkhand. Note that while our results in this section reach a level of statistical significance of $p < 0.1$ but not $p < 0.05$, Gelman & Imbens (2019) recommend avoiding reliance on higher-order polynomial fits for RD settings due to the high degree of sensitivity to the order of polynomial selected, particularly noisy treatment effect estimates, and limited statistical power. Ultimately, though, the direction and magnitude of these point estimates are consistent with the results presented earlier.

Table XI. Higher order polynomial RD Results: Reserved Election Effects on Insurgent Violence

Outcome Variable: Total Fatalities After First Reserved Elections Until 2014

Chhattisgarh (2005-14)						
Estimate	Robust Std. Error	Two-tailed P-Value	Total Units	Units Inside BW	BW	Covs.
-0.046	0.027	0.087	20,204	6,597	23.29km	Yes
-0.045	0.027	0.096	20,204	5,230	17.47km	Yes
Jharkhand (2010-14)						
Estimate	Robust Std. Error	Two-tailed P-Value	Total Units	Units Inside BW	BW	Covs.
0.002	0.004	0.70	32,927	15,585	22.27km	Yes
0.002	0.004	0.55	32,927	12,848	16.70km	Yes

These estimators include the following pre-treatment, village-level characteristics: total population, Scheduled Tribe population, Scheduled Caste population, number of literate residents, male population, primary school indicator, middle school indicator, presence of community social facilities, “main work” population, “total work” population, cultivator population, paved road indicator, mud road indicator, domestic-use electricity availability indicator, medical facility indicator, well water indicator, bank facility indicator.

G RD estimates on regions where Scheduled Area boundaries do not coincide with geological features and colonial infrastructure

Despite the historical record demonstrating the plausibility of our RD identification assumptions, an additional robustness check entails visually inspecting the location of the Scheduled Area boundaries and identifying where the boundaries potentially coincide with an abrupt change in geological characteristics or colonial infrastructure (i.e. railways), such that a Scheduled Area boundary was placed with respect to characteristics of specific settlements.

We first investigate these characteristics of Chhattisgarh. First, we generated a map which shades the Scheduled Areas in light red and superimposes them on a topographical map extracted from Google Maps. We present three versions of this map. One shows at the entire state of Chhattisgarh (Figure 5), while the other two zoom in on the northern (Figure 6) and southern (Figure 7) halves of the state, respectively. Notably, there aren't any rivers which coincide with the Scheduled Area boundaries.

Chhattisgarh Scheduled Areas and Terrain Overlay
Whole State

Figure 5. Terrain and Scheduled Areas in Chhattisgarh (whole state view)

Chhattisgarh Scheduled Areas and Terrain Overlay

Northern Half of State (Scheduled Areas shaded in light red)

Figure 6. Terrain and Scheduled Areas in Chhattisgarh (north zoom)

Chhattisgarh Scheduled Areas and Terrain Overla Southern Half of State (Scheduled Areas shaded in light red

Figure 7. Terrain and Scheduled Areas in Chhattisgarh (south zoom)

One potential area of concern is a discontinuous change in mountainous terrain in southern Chhattisgarh at the boundary of Narayanpur subdistrict and Kanker district, a border which also serves as a Scheduled Area boundary. We highlight Narayanpur and the adjacent subdistricts within Kanker in blue and orange in Figure 8, where orange refers to the non-Scheduled Area along this potentially problematic boundary, and blue refers to the Scheduled Area along this potentially problematic boundary. So, as a robustness check we exclude the highlighted sub-regions along this potentially problematic boundary and then implement our RD estimator on the remaining observations. The results using `rdrobust` in Table XII are statistically significant at the $p < 0.1$ level and consistent with the estimates we reported in the paper. The RD estimator employs an MSE-optimal bandwidth of 16.94km derived for this particular subsample.

Chhattisgarh Scheduled Areas and Terrain Overlay

Whole State (excluded districts in blue (SA) and orange (non-SA))

Figure 8. Terrain and Scheduled Areas in Chhattisgarh (excluded subdistricts highlighted)

Table XII. RD Results for Chhattisgarh (excluding potentially problematic boundaries due to topographical features)

Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
-0.042	[-0.086, 0.003]	0.069	19,766	4,865	16.94km	Yes

We also assess whether the Scheduled Area boundaries coincided with already-constructed colonial infrastructure, most notably the extensive British Indian railway system constructed in the subcontinent. Replication data from Donaldson (2018) includes detailed geospatial information indicating the precise location of the railway network in British India. The author constructed this dataset by relying on thousands of archival documents created during the British colonial era in South Asia. Using this author's geospatial data, we superimpose the colonial era railway network information on the map of Chhattisgarh's Scheduled Areas in Figure 9. We provide two additional maps — Figures 10 and 11 — which zoom in on the northern and southern halves of Chhattisgarh, respectively. While the British Indian railway line in northern Chhattisgarh appears to cross into roughly equal portions of Scheduled and non-Scheduled Areas near the Scheduled Area boundary

— implying covariate balance — it is possible (though unlikely) that this particular sub-region may be confounded. The railway near the southern Scheduled Areas of Chhattisgarh are well outside the bandwidth used for our RD, suggesting that the railway’s presence does not pose an issue for us in that particular part of Chhattisgarh. So, we estimate the RD in Chhattisgarh by excluding those observations which are in the northern half of Chhattisgarh. The results of this robustness check are in Table XIII and indicate a point estimate which is still statistically significant and its magnitude is nearly double that which we detected for the overall RD analysis in Chhattisgarh.

Chhattisgarh Scheduled Areas and Colonial-Era Railways

Whole State (railway lines in blue, Scheduled Areas in light red)

Figure 9. Colonial Railways and Scheduled Areas in Chhattisgarh

Chhattisgarh Scheduled Areas and Colonial-Era Railways Northern Half of State (railway lines in blue, Scheduled Areas in light red)

Direct distance from Bilaspur to Korba is ~85km. Our MSE-optimal BW is 23.29km.

Figure 10. Colonial Railways and Scheduled Areas in Chhattisgarh (north zoom)

Chhattisgarh Scheduled Areas and Colonial-Era Railways Southern Half of State (railway lines in blue, Scheduled Areas in light red)

Direct distance from Raipur to Dhamtari is ~65km. Our MSE-optimal BW is 23.29km.

Figure 11. Colonial Railways and Scheduled Areas in Chhattisgarh (south zoom)

Table XIII. RD Results for Chhattisgarh (excluding potentially problematic boundaries due to railway location)

Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
-0.112	[-0.214, -0.010]	0.031	12,448	4,187	25.35km	Yes

Finally, we estimate RD treatment effects in Chhattisgarh excluding the northern districts potentially (though unlikely) confounded by the railway as well as the southern district/subdistrict potentially confounded by the abrupt change in topography at the Scheduled Area boundary. The results in Table XIV are completely consistent with the main results presented in the paper.

Table XIV. RD Results for Chhattisgarh (excluding potentially problematic boundaries due to railway location and terrain)

Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
-0.066	[-0.145, 0.013]	0.101	12,010	3,086	19.54km	Yes

We apply the same approach to detecting potentially problematic Scheduled Area boundaries in Jharkhand. Figure 12 shows Jharkhand's Scheduled Areas in light red, superimposed on a topographical map extracted from Google Maps. We do not observe any potentially problematic boundaries which coincide with bodies of water or abrupt changes in topographical characteristics.

Jharkhand Scheduled Areas and Terrain Overlay Whole State

Figure 12. Terrain and Scheduled Areas in Jharkhand

Next, we superimpose the colonial-era railroad information from Donaldson (2018) to discern whether Jharkhand's Scheduled Area boundaries coincide with this infrastructure. Examining Figure 13, we find that there are not any substantial distances for which the Scheduled Area boundary appears to be drawn directly alongside — or near but on one side or the other of — a railway line, suggesting that the Scheduled Area and non-Scheduled Area settlements within Jharkhand are comparable near the Scheduled Area boundaries with respect to colonial era infrastructure.

Jharkhand Scheduled Areas and Colonial-Era Railways Whole State (railway lines in blue, Scheduled Areas in light red)

Figure 13. Colonial Railways and Scheduled Areas in Jharkhand

H RD Estimates Using “Rugged Terrain” Scheduled Area Boundaries

We conduct a further robustness check by focusing on the Scheduled Area boundaries drawn in relatively rugged and mountainous regions in the two states of interest. Our justification for doing so relates to the drawing of the Scheduled Area boundaries and the plausibility of our identification assumptions. Specifically, while the historical record suggests that the Scheduled Area boundaries in Jharkhand and Chhattisgarh were not initially drawn with respect to the characteristics of specific localities, we argue that this assumption is even more defensible in mountainous regions where the state’s reach was extremely limited and the local population largely illegible to state institutions.

To identify the subset of regions within Chhattisgarh and Jharkhand that are relatively rugged/mountainous, we estimated the ruggedness of each district in the two states and then focused our RD estimation on those districts which were in the top half on this ruggedness index. To estimate a district’s rugged terrain, we relied on the most recent release of the PRIO-GRID dataset initially developed in Tollefsen, Strand & Buhaug (2012). This dataset is a vector grid network with a resolution of 0.5 by 0.5 decimal degrees covering the entirety of earth. Using spatial coordinates for each cell in the PRIO-GRID dataset, we determined which cells are located within each of Chhattisgarh and Jharkhand’s districts. Then, using the “mountain_mean” variable — which measures the proportion of mountainous terrain within a cell based on elevation, slope and local elevation range, taken from a high-resolution mountain raster developed for UNEP’s Mountain Watch Report — we estimated the average “ruggedness” of terrain within a district. Then, we subsetted our village level dataset of insurgent violence by dropping villages which are located in districts within the bottom half of the ruggedness index. We estimated the treatment effects using `rdrobust`. The results in Table XV are consistent with those in the main body of the paper, and furthermore, the magnitude of the point estimate in Chhattisgarh’s rugged districts is even larger than when focusing on all districts.

Table XV. “Rugged Terrain” RD Results: Reserved Election Effects on Insurgent Violence

Outcome Variable: Total Fatalities After First Reserved Elections Until 2014

Chhattisgarh (2005-14)						
Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
-0.163	[-0.319, -0.007]	0.040	9,582	3,541	29.217km	Yes
-0.151	[-0.307, 0.004]	0.056	9,582	3,982	33.49km	No
Jharkhand (2010-14)						
Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
0.005	[-0.018, 0.027]	0.686	13,606	6,437	24.55km	Yes
0.005	[-0.018, 0.028]	0.647	13,606	6,501	24.93km	No

The covariate-adjusted RD estimates include the following pre-treatment, village-level characteristics: total population, Scheduled Tribe population, Scheduled Caste population, number of literate residents, male population, primary school indicator, middle school indicator, presence of community social facilities, “main work” population, “total work” population, cultivator population, paved road indicator, mud road indicator, domestic-use electricity availability indicator, medical facility indicator, well water indicator, bank facility indicator.

I RD Estimates for Jharkhand's Districts With Covariate Balance

The RD estimates for Jharkhand reported in the main body of the paper incorporated covariates for precision gains and also adjusted for any pre-treatment characteristics which exhibited imbalance across treatment and control. While the null results are consistent across the inclusion or exclusion of the imbalanced pre-treatment covariates, we conduct a further robustness check on Jharkhand in particular, where we remove all observations from one district — Godda district in the northeastern part of the state. Among the remaining districts, we conclude that there is superior balance on pre-treatment covariates for this sample compared to the full sample (see Table XVII). Table XVI reports results from `rdrobust` on this subset of settlements and indicates that there is no effect of reservations on violence in Jharkhand, consistent with our original estimates.

Table XVI. Jharkhand RD Results Using Districts with Covariate Balance: Reserved Election Effects on Insurgent Violence

Outcome Variable: Total Fatalities After First Reserved Elections Until 2014

Jharkhand (2010-14)						
Estimate	Robust 95% CI	Robust P-Value	Total Units	Units Inside BW	BW	Covs.
0.003	[-0.006, 0.011]	0.540	30,610	15,227	26.82km	Yes
0.001	[-0.008, 0.010]	0.816	30,610	14,316	24.67km	No

The covariate-adjusted RD estimates include the following pre-treatment, village-level characteristics: total population, Scheduled Tribe population, Scheduled Caste population, number of literate residents, male population, primary school indicator, middle school indicator, presence of community social facilities, “main work” population, “total work” population, cultivator population, paved road indicator, mud road indicator, domestic-use electricity availability indicator, medical facility indicator, well water indicator, bank facility indicator.

Table XVII. Balance Test: Jharkhand's Balanced Districts

Pre-Treatment Covariate	Estimate	95% CI	P-Value
ST Population	23.709	[-6.644, 54.062]	0.126
Total Population	78.480	[-51.323, 208.284]	0.236
SC Population	12.139	[-10.375, 34.653]	0.291
Literacy	36.111	[-42.427, 114.650]	0.367
Male Population	43.940	[-26.235, 114.115]	0.220
Primary Schools	-0.013	[-0.067, 0.042]	0.642
Paved Rds.	-0.010	[-0.065, 0.046]	0.733
Power Supply	-0.068	[-0.119, -0.017]	0.01

J Testing Potential Spatial SUTVA Violations

There exist threats to geographic RD validity from spillover (or SUTVA) violations because the treated and control units are, by construction, arranged cheek by jowl in geographic space. Specifically, if the treatment status of some unit i affects the potential outcomes of a neighboring unit j , then an effect estimated by comparing the outcomes of unit i under treatment and unit j under control are not causally identified (Rubin, 1986). In our framework, the processes most likely to cause SUTVA violations are either migration across the Scheduled Area boundaries, or strategic adaptation by Naxalite rebels, who shift their fixed quantum of violence-producing resources to more favorable territory *in response to treatment*. We evaluate both potential spatial SUTVA violations.

No gold-standard method for geographic spillover detection exists for non-experimental designs,¹³ and so we look for evidence of geographic spillover by re-estimating our main RD specification on various “censored” datasets. We construct these datasets by deleting observations falling within k kilometers of the cut point and retaining all other observations within the bandwidth. If treatment spillover were contaminating our estimate to a substantial degree, we would expect that the coefficient estimates in censored samples would be substantially different from our main specification, given that the censored samples delete the units most likely to be “contaminated.”

Figures 14 and 15 show that our main specification is robust to the deletion of the most likely-to-be-contaminated units on both the treatment and control sides of the Scheduled Area boundaries. Censored control units in Figure 14 show little deviation from the main specification for any deletion bandwidth. If anything, Figure 14 suggests that deleting the potentially contaminated control units results in an estimated treatment effect larger than the main results presented earlier, albeit with a substantial decrease in precision. In Figure 15 as well, all estimates on restricted sub-samples show either a similar or higher-magnitude point estimate compared to the main specification reported earlier. All restricted sub-samples, however, show similar or higher-magnitude point estimates compared to the main specification. Overall, these checks suggest that the main effect we report above is robust, and perhaps conservative given geographic spillover.

¹³For methods designed to detect spatial spillover in experimental settings, however, see Sinclair, McConnell & Green (2012)).

Figure 14. RDRobust point estimates for geographically-deliniated sub-samples, deleting between 0 and 5 km-worth of control villages.

Figure 15. RDRobust point estimates for geographically-deliniated sub-samples, deleting between 0 and 5 km-worth of treated villages.

K RD Estimates at Placebo Cutpoints

We also use `rdrobust` to estimate a local average treatment effect at various “placebo” cutpoints, and find that at most points, the effect of a cutoff around the placebo threshold is either insignificant, or consistent with the main effect we estimate at the true cutoff (Figure A.1). When large numbers of units that are in reality “treated” are assigned to control, we see a significant and positive association between treatment and violence levels. Given that violence is known to be higher deep in scheduled areas for reasons that have little to do with democratic reforms—the least reachable forest areas in Chhattisgarh are deep within scheduled areas and also happen to be the territorial bases of the insurgency—we do not interpret this association as particularly problematic for our theory.

Figure A.1. Regression discontinuity estimates at placebo boundaries ranging from 10km into Scheduled Areas to 10km out of Scheduled Areas.

L Difference-in-Differences Estimation

We complement the RD estimates with an additional robustness check: difference-in-differences estimation. This entailed estimating the effect of the reservation treatment on the pre- to post-treatment change in violence levels. Specifically, we regress $Y_{posttreattotal} - Y_{pretreattotal}$ on a treatment indicator D along with a series of covariates. $Y_{posttreattotal}$ refers to the total number of fatalities after the first reserved panchayat elections, and $Y_{pretreattotal}$ refers to the total number of fatalities in the years prior to the first panchayat elections. Our estimator also incorporates sub-district fixed effects. We apply this estimator to the entire sample of settlements in each state along with four separate windows around the Scheduled Area boundary. The difference-in-differences results for Chhattisgarh and Jharkhand are in Tables XVIII and XIX, respectively, and they are consistent with the estimates produced in our main RD analyses as well as in the RD robustness checks.

Table XVIII. Difference-in-Differences Estimation (Chhattisgarh)

	1km window	5km window	20km window	30km window	Full Sample
Treatment	−0.04 (0.02)	−0.09 (0.06)	−0.04 (0.02)	−0.04 (0.02)	−0.04 (0.02)
TOT_P	−0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
P_ST	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
P_SC	−0.00 (0.00)	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
P_LIT	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)
P_SCH	−0.02 (0.02)	0.00 (0.07)	0.00 (0.02)	0.01 (0.02)	−0.00 (0.01)
M_SCH	−0.01 (0.01)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	−0.01 (0.01)
COMM_FAC	0.01 (0.02)	−0.01 (0.05)	−0.05 (0.03)	−0.03 (0.02)	−0.01 (0.02)
MAINWORK_P	−0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.00 (0.00)
TOT_WORK_P	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
MAIN_CL_P	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)
APP_PR	0.00 (0.06)	0.17 (0.16)	0.11 (0.07)	0.09 (0.05)	0.08 (0.03)
APP_MR	−0.02 (0.06)	0.16 (0.13)	0.10 (0.06)	0.06 (0.04)	0.03 (0.03)
APP_NAVRIV	0.01 (0.06)	0.10 (0.06)	0.01 (0.03)	0.01 (0.02)	−0.01 (0.01)
POWER_DOM	0.03 (0.03)	−0.05 (0.07)	−0.00 (0.03)	0.01 (0.02)	0.02 (0.02)
TOT_M	0.00 (0.00)	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
MEDI_FAC	−0.02 (0.02)	0.03 (0.02)	0.01 (0.02)	0.01 (0.01)	0.01 (0.01)
WELL	0.04 (0.04)	0.13 (0.09)	0.02 (0.04)	0.03 (0.03)	0.03 (0.04)
BANK_FAC	0.01 (0.02)	−0.03 (0.06)	−0.02 (0.05)	−0.01 (0.04)	−0.01 (0.02)
R ²	0.15	0.04	0.03	0.03	0.02
Adj. R ²	0.01	0.01	0.02	0.02	0.02
Num. obs.	410	1768	5809	8201	20204
RMSE	0.21	0.81	0.69	0.70	0.99

All estimators include sub-district fixed effects. HC2 robust standard errors in parentheses.

Table XIX. Difference-in-Differences Estimation (Jharkhand)

	1km window	5km window	20km window	30km window	Full Sample
Treatment	0.06 (0.04)	0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	0.01 (0.00)
TOT_P	-0.01 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
P_ST	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
P_SC	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
P_LIT	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
P_SCH	0.06 (0.06)	0.01 (0.01)	-0.00 (0.00)	-0.00 (0.00)	-0.01 (0.00)
M_SCH	0.10 (0.08)	0.03 (0.03)	0.00 (0.00)	-0.00 (0.01)	0.00 (0.01)
COMM_FAC	0.06 (0.06)	0.03 (0.02)	0.01 (0.01)	0.01 (0.01)	0.02 (0.01)
MAINWORK_P	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
TOT_WORK_P	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
MAIN_CL_P	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
APP_PR	-0.07 (0.06)	0.00 (0.01)	0.01 (0.01)	0.00 (0.00)	0.00 (0.01)
APP_MR	0.03 (0.03)	0.02 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
APP_NAVRIV	-0.01 (0.05)	0.01 (0.02)	-0.02 (0.01)	-0.02 (0.01)	-0.02 (0.01)
POWER_DOM	0.15 (0.11)	-0.01 (0.03)	-0.00 (0.01)	-0.00 (0.00)	-0.00 (0.01)
TOT_M	0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
MEDI_FAC	-0.00 (0.03)	0.01 (0.01)	-0.00 (0.01)	0.00 (0.01)	-0.01 (0.01)
WELL	0.04 (0.04)	-0.00 (0.01)	0.00 (0.00)	0.00 (0.00)	-0.01 (0.00)
BANK_FAC	0.01 (0.06)	-0.04 (0.02)	0.00 (0.01)	-0.00 (0.01)	0.01 (0.01)
R ²	0.54	0.08	0.02	0.02	0.01
Adj. R ²	0.52	0.07	0.02	0.01	0.00
Num. obs.	972	4581	14598	18783	32927
RMSE	0.27	0.22	0.21	0.21	0.31

All estimators include sub-district fixed effects. HC2 robust standard errors in parentheses.

M Salwa Judum and Civilian Victimization

In many non-Scheduled Areas in Chhattisgarh, non-Tribal local elites were killed for their involvement in the Salwa Judum, an anti-Naxal citizens' militia formed in the early 2000s and accused of carrying out human rights atrocities against innocent civilians in Chhattisgarh. However, these killings did not occur because the Salwa Judum members were suspected of being informants. For example, a former lower caste (non-Tribal) sarpanch in a non-Scheduled Area had been killed in October 2005 for participating in and carrying out operations as part of the Salwa Judum (ACHR, 2006: p. 31). To reiterate, sarpanches and other panchayat officials killed outside of Scheduled Areas actively participated in the Salwa Judum campaign but were not suspected by the rebels of passing along sensitive information to counterinsurgent forces about rebels' operations.

N State Legitimacy Geographic RD Results

We evaluate whether ST reservations improved state legitimacy in Scheduled Areas with an additional geographic RD specification using voter turnout as the outcome variable. If the state's legitimacy increased in Scheduled Areas, then we might expect participation in “official” political processes to be higher than in nearby non-Scheduled Areas. We measure this outcome with booth-level vote totals for Chhattisgarh's 2018 state election, scraped from official Form 20 documents. Booths are the smallest geographic unit for which votes are tabulated and often correspond to individual villages. Merging booth-level vote totals with a shape file containing coordinates for all booths in Chhattisgarh (Susewind, 2014), we measure the distance of each booth to the nearest Scheduled Area boundary. RD results in Table XX suggest that reservations had no effect on votes cast in Scheduled Areas versus non-Scheduled Areas.

Table XX. RD Results: Reserved Election Effects on State Legitimacy (Chhattisgarh)

Estimate	95% CI	P-Value	Total Units	Units Inside BW	BW
-10.853	[-36.554 , 14.847]	0.408	21,233	5,564	17.861km

O Opportunity Costs Geographic RD Results

We estimate whether reservations affected the male employment rate in Chhattisgarh with settlement-level census data from the 2011 Census. We used the Government of India’s Primary Census Abstract which includes 2011 data on male employment for settlements in Chhattisgarh (Ministry of Home Affairs (Government of India), 2020). Using the “SHRUG” dataset from Asher et al. (2019), we merged the 2011 employment data with our original dataset containing each settlement’s distance from the nearest Scheduled Area boundary. The results are in Table **XXI** and indicate that reservations did not substantially improve the male employment rate.

Table XXI. RD Results: Reserved Election Effects on Male Employment Rate (Chhattisgarh)

Estimate	95% CI	P-Value	Total Units	Units Inside BW	BW	Covs
0.015	[-0.026, 0.055]	0.487	17,204	4,469	17.25km	Yes
0.025	[-0.01, 0.06]	0.138	17,204	6,782	28.31km	No

P Map: Treatment and Control Units

Chhattisgarh RD Villages
for MSE-optimal bandwidth of 23.29km

Figure 17. Treated vs. Control units for the main regression discontinuity specification in Chhattisgarh; 5th Schedule Areas in gray

Q Jackknife Analysis

We use jackknife resampling to probe whether outlier observations drove our RD findings in Chhattisgarh. The institutional reform of interest was implemented across a large and reasonably heterogeneous area, but it is possible that our results are driven by particularly strong treatment effects in only some sub-districts. Identifying high-leverage observations checks the validity of our effect finding, and provides a suggestive test *within* Chhattisgarh of our assertions regarding the causes of treatment effect heterogeneity between Chhattisgarh and Jharkhand.

We identify “high-leverage” observations in Chhattisgarh by jackknife resampling (Efron, 1982; Cameron & Trivedi, 2005) at the sub-district level. Jackknife resampling, a linear approximation of bootstrap resampling, estimates the parameter of interest as an average of the parameter estimates in n subsamples of the full data, where each subsample leaves out the i th observation. Though often used to estimate variance of estimators, this procedure indicates statistically important observations or groups of observations by highlighting the subsample parameter estimates that deviate most from the full-sample estimate.

We employ block-jackknife resampling—where all observations in a sub-district are dropped at once—to identify which sub-districts are high-leverage components of the RD analysis. Figure 18 shows that five sub-districts drive the size and significance of our estimated treatment effect. The sub-districts comprising Dantewada district along with a sub-district in neighboring Bastar (see Figure 19 for reference) are the “high-importance” sub-districts. These areas have typically seen the highest conflict intensity and are part of the putative strongholds of the Naxal movement in Chhattisgarh (Sundar, 2016).

The key subdistricts, in other words, are where Naxalite violence and rebel governance are most prevalent. We interpret this as supporting our primary interpretation of the RD results, because the treatment effect is driven by the geographic units that are most substantively important not by high-leverage observations resulting from noisy data. The jackknife also tentatively supports our proposition about reservations’ heterogeneous effects: electoral quotas are more likely to decrease subsequent rebel violence in places like the Dandakaranya region (Bastar and Dantewada) where pre-treatment rebel governance was most intense.

Figure 18. Jackknife resampling estimates for the Chhattisgarh RD estimates. Each row is a sub-sample re-estimation of the treatment effect, omitting the district indicated on the vertical axis. The individually-necessary subdistricts (1601-1604 and 1502) are: all sub-districts of Dantewada, and one sub-district of Bastar.

Figure 19. Map of individually-necessary subdistricts for a statistically significant effect. Villages belonging to high-importance sub-districts are indicated in yellow and green. Treatment and control villages within the RD bandwidth, but outside of the high-importance sub districts, are shown in red and blue. Black X marks of varying sizes indicate the pre-quota/post-quota difference in security force fatality levels. Areas without X marks have little difference.

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