Power-Sharing and Low-Level Conflict: Evidence from Political Reservations in India*

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Abstract

This paper analyzes the effect of an important power-sharing institution – political reservations for historically disadvantaged minorities – on low-level subnational conflict in India. Previous research has identified positive impacts of reservations on public goods provision benefitting the targeted minorities. However, reservations may come to the detriment of other groups, leading to backlash and potentially higher conflict. I empirically investigate this question with panel data from Indian districts and assembly constituencies. Exploiting exogenous variation in reservations stemming from rules in the process of apportioning reserved seats, I show that reservations consistently lead to lower levels of conflict. The combination of district- and constituency-level analysis shows that this is not a displacement effect, and that potential backlash at the district level is outweighed by direct conflict reduction. I explore mechanisms behind this result and show that (1) conflict reductions have been particularly pronounced for killings of security personnel, (2) conflict reductions have been stronger in areas with active Naxalite insurgent activity, and (3) conflict reductions were accompanied by reductions in caste-related conflict events and crimes against lower castes.

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1 Introduction

Societal conflict between ethnic, religious, or class-based groups poses a significant challenge to a wide range of countries across different regions and development levels. A widely adopted institution to reduce conflict is power-sharing: explicitly guaranteeing political representation to minority groups. Figure 1 shows that power-sharing institutions are common across the world, with 52 countries, representing 55% of the global population, having such arrangements in place (International Parliamentary Union 2025).

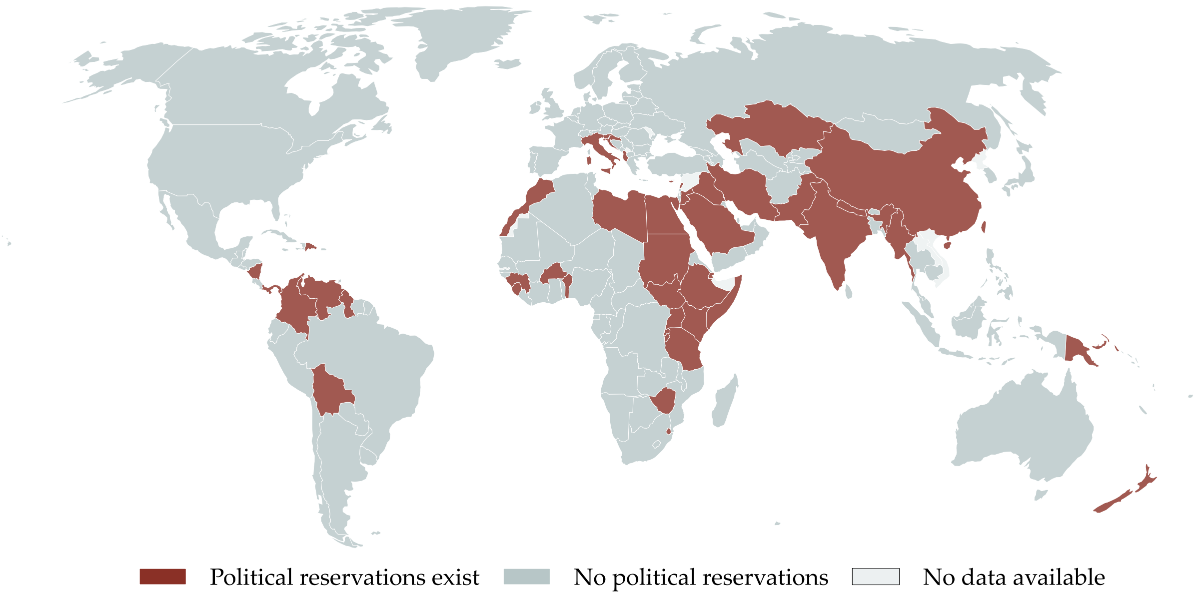


Figure 1: Countries with Power-Sharing Institutions (Source: International Parliamentary Union, manual corrections by author)

While power-sharing is common across contexts, empirical evidence on its effectiveness in reducing tensions and sustaining peace remains limited.

To anchor the discussion, consider two examples of such power-sharing institutions. First, in Northern Ireland, the Good Friday Agreement of 1998 implemented power-sharing after three decades of violent conflict between Protestant unionists and Catholic nationalists. Both communities were guaranteed a stake in government through proportional representation in parliament and the creation of a dual head of the executive, shared between one unionist and one nationalist. This system, despite occasional deadlock, is widely seen as a key factor in the peace process (see, e.g., Nagle 2018). Second, consider Lebanon, a highly fragmented nation consisting of various Christian and Muslim groups. Its constitution and the 1943 National Pact assign key parliamentary and executive positions to different groups (e.g., the President must be Maronite Christian, and the Prime Minister Sunni Muslim). While this arrangement brought initial stability, it ultimately failed and contributed to the outbreak of civil war starting in 1975 (Makdisi and Marktanner 2009).

These examples highlight the theoretical ambiguity surrounding power-sharing institutions and their effects on conflict. Power-sharing can solidify a fragile peace (as it did in Northern Ireland) or entrench existing societal divisions (as in Lebanon). On one hand, power-sharing may reduce conflict by improving representation and addressing grievances by minorities. On the other hand, it might exacerbate tensions by making group differences more salient or triggering backlash from the majority or non-targeted minorities. Thus, whether power-sharing reduces conflict is, ultimately, an empirical question.

The empirical study of the causal effects of power-sharing institutions on conflict has been limited because these institutions are typically implemented at the national level, creating a small sample of cases with limited variation and few appropriate counterfactuals for comparison. This makes it difficult to isolate the effects of power-sharing from other country-specific factors or to make generalizable claims about their effectiveness. To overcome these methodological constraints, researchers need settings with – plausibly exogenous – within-country variation in the degree of power-sharing.

India's political reservation system offers precisely such an opportunity for rigorous empirical analysis. In its 1950 constitution, India established the largest power-sharing institution in the world: political reservations for historically disadvantaged minorities, the scheduled castes (SCs) and scheduled tribes (STs). These two groups receive *reserved seats* in the state and national parliaments proportional to their population share. In these reserved constituencies, only candidates from specified groups can contest elections, but all eligible voters can vote. This maintains universal suffrage while restricting candidacy to minorities, thus ensuring their representation in the legislative branch of government.

I focus on reservations for scheduled castes, which is ideal for empirically estimating effects of power-sharing because of several unique features: First, these reservations are implemented based on geography – certain constituencies get allocated a reserved seat for several legislative periods. Second, they are also time-varying: To adjust for changing population shares, the reserved seats are reallocated periodically through a process called *redistricting*. This variation across space and time that can be exploited to estimate the effect of additional minority representation on conflict, keeping the overall institutional environment constant. Third, unlike reservations for scheduled tribes (that are geographically limited to areas with large tribal populations), reservations for scheduled castes are spread across all of India, making the results more broadly representative and externally valid.

Beyond this advantage for empirical identification, India's reservation system provides a compelling substantive context for studying power-sharing institutions. Conflict reduction was not an explicit goal when reservations were established abd the constituent assembly primarily aimed to address economic disadvantage and social discrimination. However, India's subsequent experience with communal riots, insurgencies, and sectarian movements has inadvertently tested these institutions' capacity to reduce tensions and appease different groups. The Indian context also offers insights that may translate to other settings, despite caste being often viewed as unique to South Asia. Across the world, power-sharing institutions are based on religion (such as in Lebanon), political divisions (Northern Ireland), ethnicity (Bosnia and Herzegovina), gender, or class. Caste intersects with class hierarchies, has religious dimensions, and functions analogously to ethnicity in other contexts (see, e.g., Chandra 2004), making it relevant for understanding other identity-based power-sharing arrangements. Furthermore, India's experience is a micro-cosm for broader debates about mandated representation: reservations have sparked violent protests when expanded to new groups via the Mandal Commission in 1990, led to violent backlash against elected lower-caste officials in some cases Narula 1999; Acemoglu and Robinson 2019, and triggered unrest from communities demanding inclusion in reserved categories Times of India 2016; NDTV India 2016. Simultaneously, evidence suggests reservations can reduce grievances by improving public goods provision for vulnerable populations Chattopadhyay and Duflo 2004. This tension between potential conflict escalation and grievance redress makes India an ideal setting for the first systematic analysis of how political reservations affect low-level societal conflict.

In this paper, I attempt to answer the following research question: **How do mandated political reservations for disadvantaged minorities affect the incidence and intensity of low-level conflict in India?** I specifically examine whether increasing Scheduled Caste representation in state legislatures reduces or exacerbates various forms of societal tension, including violent incidents, protests, and crimes against lower castes. This question is important not only for understanding India's largest affirmative action program but also for informing broader debates about whether power-sharing institutions alleviate or intensify group-based conflicts.

For my empirical analysis, I combine novel administrative data on the apportionment of – geographically fixed – reserved seats for Indian state assembly constituencies with geographically disaggregated conflict data. I isolate effects of reservations on conflict due to exogenous variation in reservations based on two rules in the most recent Indian re-allocation of reservations in 2008.

First, I consider the apportionment of reserved seats to districts: While official rules stipulate that every district shall receive a number of reserved constituencies that is proportional to the population share of scheduled castes, this is not possible in practice because the actual number of reserved constituencies is necessarily integer. Therefore, I exploit the fact some districts received an additional reserved seat purely because of rounding constraints. I combine this with the staggered roll-out of the first election after the delimitation between 2008 and 2012. In a differences-in-differences design, I estimate the effect of an additional reserved seat within a district on district-level conflict outcomes from Fetzer (2020) and crime against members of the Scheduled castes, from official Indian crime statistics. Across all outcomes, I find that reservations robustly *reduced* conflict and crime against SC members.

Second, I zoom into districts and consider how reserved seats were allocated to assembly constituencies:[1] Constituencies were ranked within districts by their population share of SC members, and reservations were then apportioned starting from the highest SC-share constituency until the fixed number of reserved seats in the district was reached. This procedure allows me to compare the conflict outcomes of constituencies just above and below the cutoff. I estimate the effect of reservations on conflict at the constituency level using geographically disaggregated conflict data from ACLED (Raleigh et al. 2010). Once again, I find that reservations have *reduced* conflict across a range of outcomes. This remains the case if I restrict the outcome to events related to caste-based conflict.

The fact that I am able to exploit exogenous variation in reservations at the district and at the assembly constituency level allows me to speak to broader general-equilibrium effects. Reservations at the smaller constituency level have reduced conflict, and the fact that conflict has also decreased at the larger geographic district-level suggests that this local conflict reduction outweighs any potential negative spillover effects. In other words, the conflict reduction in reserved constituencies is not merely a conflict *displacement*, and there is no large backlash in unreserved constituencies.

Finally, I shed some light on the mechanisms behind this conflict reduction. By disaggregating the regressions by conflict type, I show that conflict reductions have been particularly pronounced for killings of militants. Looking at the spatial distribution of conflict over India, I show how conflict reductions have been stronger in areas with active Naxalites, India's largest insurgency group. This suggests that reservations reduce conflict because they reduce grievances. I also study the effect of reservations on crimes against lower castes and find that, mirroring the overall effect on conflict, crimes have decreased in districts with more reservations. I also restrict the analysis at the constituency-level to conflict events related to caste identities, and find similar reductions in conflict. Taken together, the last two results suggest that reservations have not increased inter-communal tensions at the local level, providing some evidence against a backlash story.

This study adds to the existing literature in several ways:

Firstly, it is closely related to a large literature that analyzes outcomes of affirmative action (AA) policies, and in particular of political power-sharing through mandated political representation. The large literature on AA policies is reviewed in Holzer and Neumark (2000), who conclude that AA is effective in redistributing employment and education opportunities to the groups it addresses. While there is widespread fear

[1] Assembly constituencies are fully contained within districts. Districts contain on average seven assembly constituencies.

that AA leads to efficiency losses, they do not find strong evidence for such losses in the literature. For India, Bertrand et al. (2010), Deshpande and Weisskopf (2014), and Bhavnani and Lee (2019) have analyzed the effects of reservations in the education system and the public sector, with mixed findings on its efficiency. This paper focuses on political reservations, an increasingly popular instrument to mandate political representation of minorities and to achieve equity through power-sharing. Today, more than 100 countries use such reservations to guarantee women, ethnic minorities, and other groups seats in national or subnational parliaments (Krook and O'Brien 2010; Hughes 2011). For India, previous research has analyzed several outcomes of political reservations, notably the provision of public goods (Pande 2003, Chattopadhyay and Duflo 2004, Besley, Pande, et al. 2004, Dunning and Nilekani 2013), poverty (Chin and Prakash 2011), the delivery of public employment programs (Gulzar et al. 2020), and changes in stereotypes and discrimination (Beaman et al. 2009, Bhavnani 2009, Bhavnani 2017, O'Connell 2020). More recently, several studies have considered potential adverse consequences of political reservations, such as crime against lower castes (Girard 2016) and women (Iyer, Mani, et al. 2012) as well as redistribution at the expense other minorities or of the majority population (Sharan and Kumar 2019, Gulzar et al. 2020). While the literature has found that reservations have increased the provision of public goods and led to more pro-poor policies, the evidence on changing stereotypes and crime is mixed. In this paper, I analyze low-level conflict, which allows both the minority and other groups to react to reservations and helps me estimate overall effects on conflict outcomes.

Secondly, this paper also adds to the literature on subnational conflict in India: Though India never experienced a full-fledged civil war after its independence, it continues to be affected by multiple civil conflicts, in particular Hindu-Muslim riots (Varshney 2002; S. Wilkinson 2004; Mitra and Ray 2014) and the Naxalite rebellion (Vanden Eynde 2018). Most of these studies highlight income-based explanations of conflict, according to which negative income shocks increase conflict through lowering its opportunity cost (Collier and Hoeffler 1998; Collier and Hoeffler 2004; Miguel et al. 2004; Dube and Vargas 2013, for Hindu-Muslim riots Bohlken and Sergenti 2010; Mitra and Ray 2014, for the Naxalite conflict Vanden Eynde 2018; Fetzer 2020). Previous studies on conflict in India rely on spatially relatively coarse data on conflict at the state or district level. I overcome this constraint by using the ACLED data, which is available at the town/subdistrict level (Raleigh et al. 2010). This allows me to analyse reservations for state constituencies, but comes at the cost that I can not use temporal variation in the reservations. This study is also related to the literature on ethnicity and subnational conflict (Fearon and Laitin 2003; Montalvo and Reynal-Querol 2005): In a cross-country panel, Fearon, Kasara, et al. (2007) find no evidence for the hypothesis being ruled by the member of an ethnic minority increases the onset of civil conflict. I complement this debate by presenting estimates for the effect of political reservations on conflict on two different subnational levels.

Finally, this paper is grounded in a long and distinguished political economy literature on the effects of elections – and electoral incentives – on political and economic outcomes (Besley and Case 1995; Persson and Tabellini 2000; Ferraz and Finan 2011). Elections have the potential to prevent radical effects of reservations by making minority politicians implement desirable policies for the majority to secure reelection. In this spirit, Dunning and Nilekani (2013) find that reservations at the local level in India did not have sizeable redistributive effects because of the presence of multi-ethnic parties and dynamic incentives of politicians. I add to this literature and show that the identity of elected politicians matters and influences the level of low-level conflict we observe.

The rest of the paper is organized as follows: Section 2.1 gives a brief overview of the political reservation system, the main institutions analysed in this study, and internal conflict in India. Section 3 presents data, identification strategy, and results of the district-level analysis. Section 4 presents data, identification strategy, and results of the constituency-level analysis. Section 5 explores the empirical drivers behind the results, and section 6 concludes.

2 Context

Before presenting the empirical analysis, this section highlights some additional details helful for the understanding of the institutional context of political reservations in India.

2.1 Power-sharing and political reservations in India

The Indian caste system is a millenia-old system of social stratification that continues to persist until today and that is characterized by strong discrimination against lower castes and *dalits*, groups outside of the traditional caste hierarchy. With the goal to improve the economic and social situation of these groups, the Indian Constitution laid the ground for one of the world's oldest and most extensive systems of power-sharing via special provisions for Scheduled Castes (SC; the lower castes and *dalits*) and Scheduled Tribes (ST; indigenous people). While these provisions were initially planned to be temporary, they have been extended and deepened over the last decades.

Despite a history of over 70 years of power-sharing, recent experimental studies confirm that there is still widespread discrimination against lower castes (Siddique 2011). Individuals from lower castes also face disadvantages in the political system: While SCs and STs constitute 16.6% and 8.6% of the population, respectively, candidates from these groups win only about 0.5% and 1.6% of non-reserved legislative assembly seats. This relation is shown in Table 1.

To overcome these disparities, India introduced so-called *political reservations* on all lev-

Table 1: Assembly elections: Seats won by caste, 2014-2018

	All constituencies		Unreserved		Reserved	
	Number	Percent	Number	Percent	Number	Percent
General	2386	71.87	2386	97.95		
SC	509	15.33	11	0.45	498	56.33
ST	425	12.80	39	1.60	386	43.67
Total	3320	100.00	2436	100.00	884	100.00

els of political decision making. These reservations, currently in place for SCs, STs and women, restrict candidacy for certain political positions to members of the designated group, while the electorate remains unrestricted. Reservations for the Members of Parliament (MP: national level) and Members of Legislative Assemblies (MLA: state level) have been in place since the 1951 election. Over time, the proportion of reserved seats in the lower house of the national parliament has increased from 20% to around 24%, reflecting their relative increase in the population share. The assignment of constituencies to a reservations status changes only when constituency boundaries are redrawn in a delimitation process; the last two such delimitations were implemented in 1974 and 2008.

In this paper, I focus on reservations for seats in the state legislatures, i.e., for MLAs. Ample evidence shows that MLAs are politically and economically important and have the power to influence political and economic outcomes. India's federal structure gives the states substantial legislative and budgetary power (Pande 2003; Rao and Singh 2003). MLAs influence policies and the budget for the state as a whole, but focus most of their work on the constituency they represent (Jensenius 2015). For example, they receive Local Area Development grants which they can distribute to finance development projects in their constituency.[2] This suggests that MLAs have the power and resources to influence state-level policies as well as the provision of public goods in their constituency (Pande 2003; Chin and Prakash 2011). MLAs are typically elected for five years, giving them substantial time to influence policy outcomes. Taken together, it is appropriate to study reservations for MLAs because their power and resources make it plausible that they affect aggregate outcomes, including conflict.

2.2 Delimitation commission

India's electoral districts are redrawn in irregular intervals to account for changes in the underlying population and correct for malapportionment. To that extent, the government sets up a "Delimitation Commission", an independent body charged with the task of drawing electoral district boundaries and allocating reserved seats in the state

[2] In Gujarat, for example, each MLA receives 15 million INR, corresponding to around 1 million US$ in purchasing power parity. In Maharashtra, the grant amounts to 20 million INR, in Uttar Pradesh to 30 million INR.

and national parliaments. The first such delimitations took part in 1952, 1962, and 1972. After that, the first (and last) delimitation was carried out in 2008, following the establishment and report of the 2002 delimitation commission.

During the 2008 delimitation process, the boundaries of India's electoral districts were redrawn, on the basis of which reserved seats were reallocated.[3] Figure 5 shows the distribution of the Scheduled Caste population, and Figure 9 the distribution of reserved seats in the state parliaments. The delimitation commission did not have a mandate for the redistricting of four States (Assam, Manipur, Nagaland, Arunachal Pradesh). For one state (Jharkhand), the delimitation commission submitted a report, but the proposed changes were not put into action (see The Economic Times 2008).

Importantly, Iyer and Shivakumar (2009) find that the 2008 delimitation commission worked largely free of political influence and showed low levels of partisan bias. They also show that the distribution of various socio-economic outcomes was barely affected by the delimitation.

In my analysis, I use the fact that the 2008 delimitation was rolled out across states in a staggered manner. The new constituency boundaries were implemented in the first state election after 2008, with all states having their first election under the new reservation allocations between 2009 and 2012.

2.3 Internal conflict in India

India has never experienced a full-fledged civil war. Nevertheless, episodes of civil conflict have shaped its history over the last decades. These include secessionist movements (such as in Jammu and Kashmir in the North, Punjab in the West, and the North Eastern states), Hindu-Muslim riots (Varshney 2002; S. Wilkinson 2004; Mitra and Ray 2014) and, most importantly, the Naxalite-Marxist insurgency (Vanden Eynde 2018).

Previous studies have emphasized how *economic* grievances are related to conflict by studying how economic inequality, shocks or addressing economic grievances affects this type of violence (Mitra and Ray 2014; Fetzer 2020; Khanna and Zimmermann 2017; Vanden Eynde 2018). However, while *political* grievances have received equal weight in Indian policy debate around these conflicts, it has not been studied whether addressing these political grievances via power-sharing can reduce conflict. This gap is particularly relevant to study because existing Indian insurgency groups have been shown to recruit from politically excluded minorities. For example, Kleinfeld and Majeed (2016) argue that Naxalites recruited insurgents from the lower castes, exploiting historic inequalities at the intersection of caste and class. The author hypothesizes that, in the state of Bihar, political empowerment, not economic redistribution alone, was

[3] The overall proportion of reserved seats increased only slightly, but there was substantial variation at the constituency level. For example, the state of Haryana received the same number of total reserved seats, but adjustments in the number of reserved constituencies were made for 16 out of 19 districts.

key to reducing Naxalite violence. Similarly, Dixit (2010) argues that social integration has been more effective than a law-and-order strategy in bringing down insurgency violence in India. While these arguments are plausible, there is no systematic evidence on the relation between political reservations and conflict.

Figure 2 below gives further suggestive evidence that extending political reservations to members of the scheduled castes may reduce conflict. It shows the average annual number of relevant conflict events per district for the years 2000 through 2023, aggregated by whether districts received fewer, more, or the same number of reserved seats in the 2008 delimitation as before. Delimitations are implemented between 2008 and 2012, indicated by vertical lines. The figure shows that, compared to districts with fewer or the same number of reserved seats, districts with more reserved seats experienced a relative decline in conflict events in the years that the delimitation was implemented. This pattern is consistent with the hypothesis that political reservations reduce conflict, but may also be driven by other factors – as the figure visualizes, districts that receive more reservations following the delimitation are already on a different conflict trend then districts that receive fewer reservations. The empirical analysis in the following sections attempts to isolate the causal effect of political reservations on conflict.

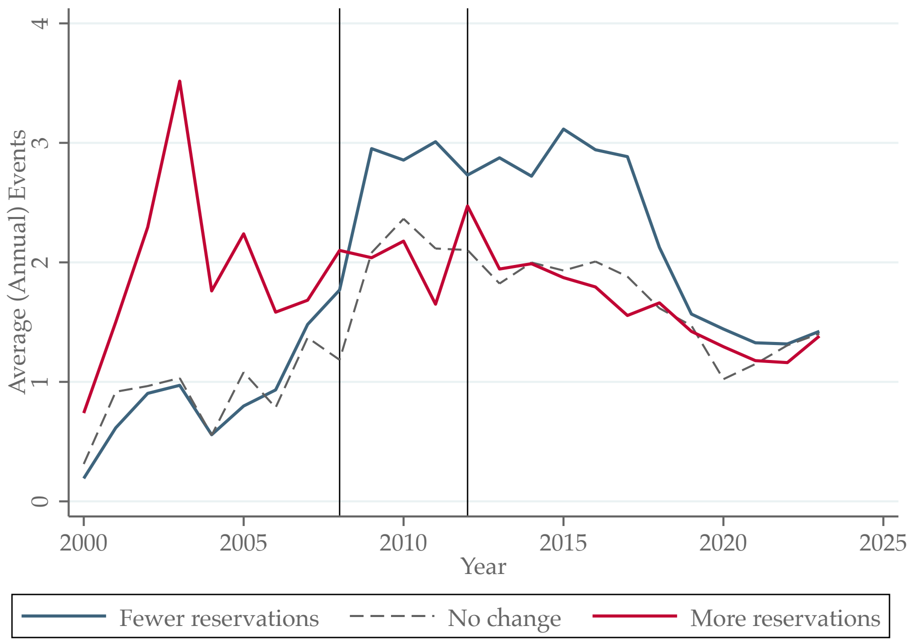


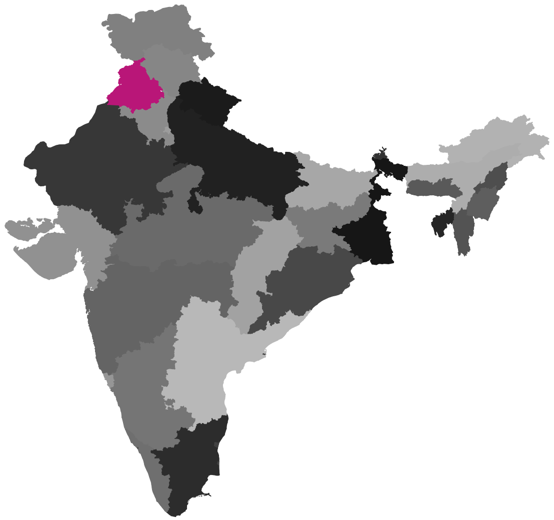
Figure 2: Average number of conflict events by change in reservation allocation to districts

2.4 Model

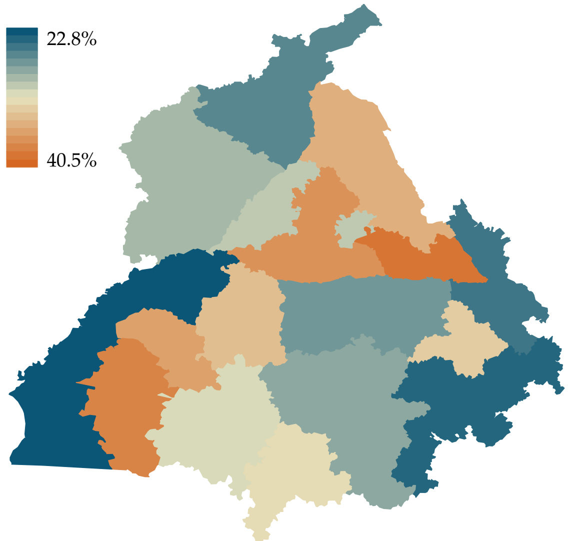
A priori, it is unclear whether political reservations decrease or increase conflict. To formalize one theoretical channel how political reservations can reduce conflict, Appendix D presents a model of reservations and conflict. Conflict arises from dissatisfaction, which is a function of the allocation of public goods by politicians. On the one hand, since the reserved groups are a minority in numbers, the reservation policy generates more losers than winners, whose backlash might lead to an observable increase in conflict. On the other hand, members of the scheduled castes are on average poorer and have a lower opportunity cost to engage in conflict, making them more sensitive to changes in policies than the relatively better-off majority. Therefore, if the minority group is relatively large and economically backward, having a reserved politician that provides public goods closer to the ideal point of the minority decreases conflict.

3 District level analysis

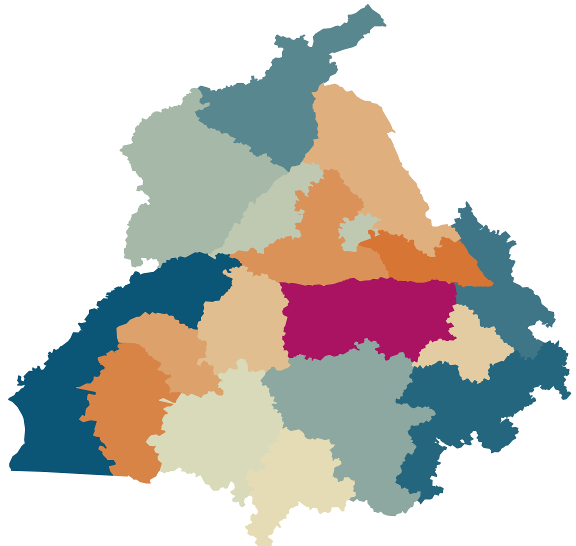
Simply comparing the outcomes of districts with more or fewer reserved assembly seats, or those reserved and unreserved constituencies may not be an appropriate strategy to identify the effect of reservations, as reserved constituencies are systematically different from unreserved ones. In particular, having a larger SC population increases the probability of a constituency to be reserved, but is empirically also associated with more conflict. To overcome this selection bias, I use plausibly exogenous variation in reservations on the district level and the constituency level. Across the description, I refer to Figure 3, which visualizes the reservation assignment procuredure that gives rise to my empirical strategy. This section discusses the district-level analysis, and section 4 discusses the constituency-level analysis.



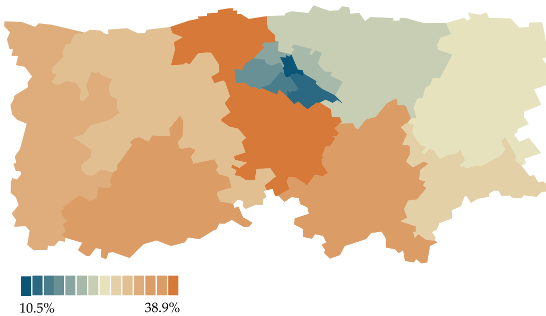
(a) Indian states, Punjab highlighted



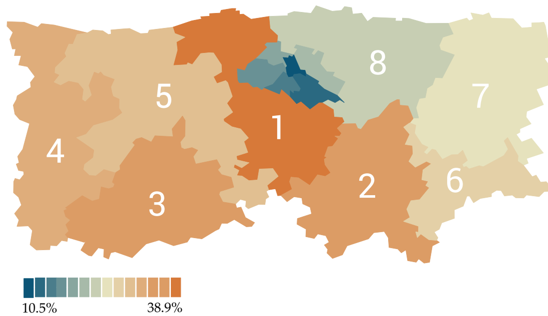
(b) Districts in Punjab by SC population share. Orange districts have a larger SC population.



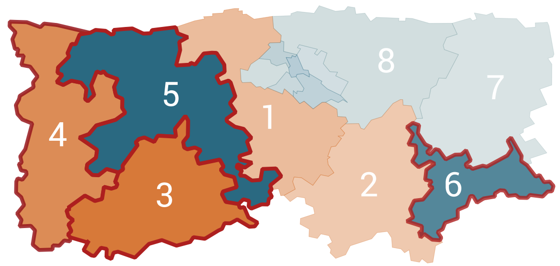
(c) Ludhiana district highlighted. 34 reserved seats in Punjab and 10.8% of Punjab's SCs give $0.108 \times 34 = 3.67 \rightarrow 4$ reserved seats. Extra seats $= 0.33$.



(d) Assembly constituencies in Ludhiana district by SC population share. Orange constituencies have large SC population.



(e) Constituencies within Ludhiana are ranked based on SC population share.



(f) Constituencies 1-4 receive reservation. Constituencies 3 and 4 serve as "treatment group", and 5 and 6 as the "control group".

Figure 3: Visualization of empirical strategy, top panel for district-level analysis, bottom panel for constituency-level analysis.

3.1 Data and empirical strategy

Reservations I collect administrative data on reservations from the Indian delimitation commission (Delimitation Commission of India 2008). This data contains information on reservations and on the scheduled caste population at the constituency level, which I then aggregate to the district level. Districts receive a number of reserved seats based on a fixed procedure. In the first step, the number of reserved seats at the state level is calculated as the rounded proportion of the SC population within the state. In the second steps, seats are allocated by district within states. The SC population in a given district, divided by the total SC population in a state, multiplied by the total number of reserved seats in a given state gives the total number of reserved seats within a district.

This rule gives rise to exogenous variation in the number of reservations across districts. Since the number of reserved seats must be integer, the expected fractional number of reserved seats is rounded up or down.[4] Therefore, districts with very similar SC shares may end up having a different number of reserved seats purely because of rounding. The top panel of Figure 3 visualizes this. For the district of Ludhiana, the formula mandates 3.67 reserved seats, which is rounded to 4, giving Ludhiana 0.33 more reserved seats than expected based on the population share of SCs. Figure 4 plots the distribution of actual reserved seats on expected fractional reserved seats, with clear jumps visible at the midpoint between two integers.

This is the base of my empirical strategy: I construct a variable, *Extra Seats*, that is the difference between the actual reserved seats and the expected fractional reserved seats, and estimate how having an extra seat because of rounding affects conflict outcomes.

Conflict data To measure internal conflict, I rely on several sources of data. First, I use annual data on subnational conflict in India collected by Fetzer (2020). The data is based on more than 40,000 newspaper articles collected by the South Asia Terrorism Portal, which is processed by Natural Language Processing methods to extract conflict parties, types, fatalities, and other characteristics for conflict events at the district level with a temporal coverage from 2000 to 2014. This is ideal for my application, as as I can observe districts both before and after the delimitation and can thus control for unobserved heterogeneity at the district and year level. I use information on the total number of conflict events, but also on the number if individuals that were killed or injured, the the number of civilians, security personnel, and militants killed in conflict events. In total, my dataset contains 239 districts with variation in conflict and killings/injuries over the sample period. Figure 5 maps the geographic distribution of the Scheduled Caste population and of conflict events across India.

[4] The numbers are adjusted to ensure that the total number of reservations within a state is as previously calculated.

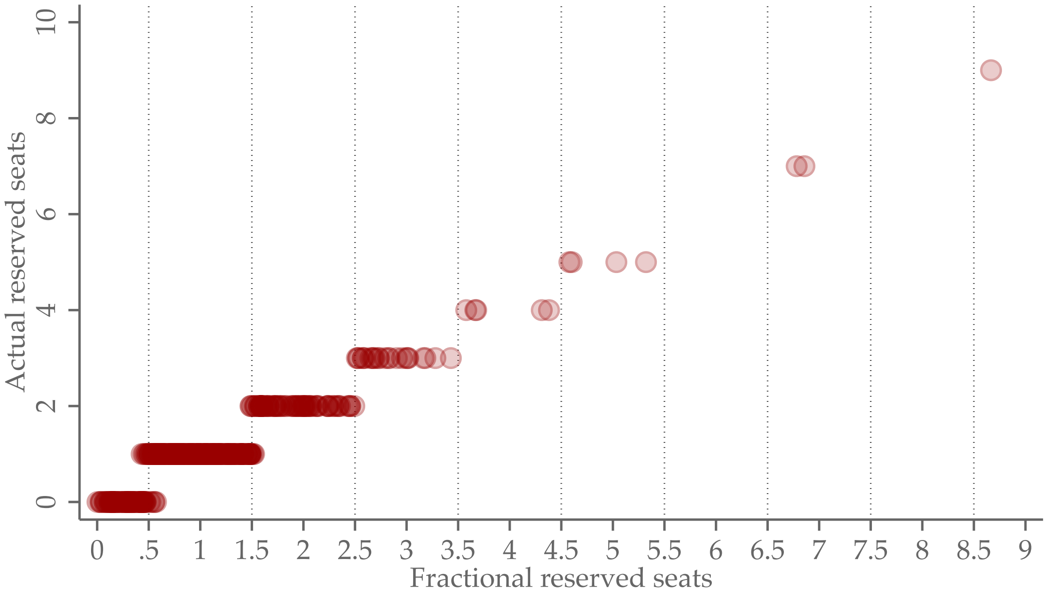
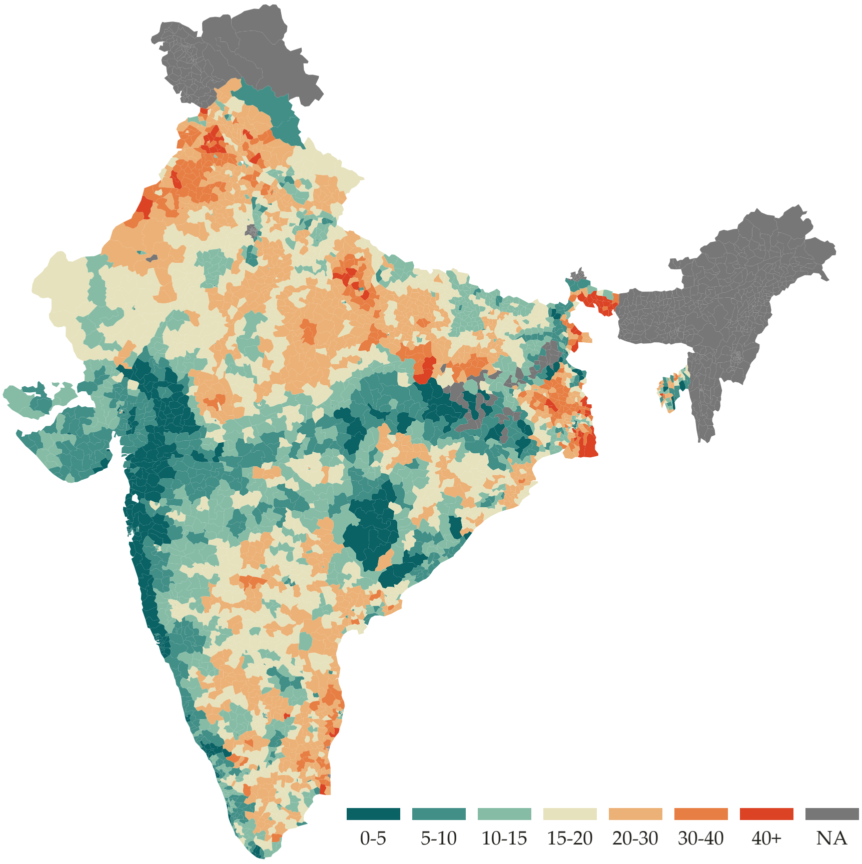


Figure 4: Visualization of district-level assignment rule. Fractional seats based on actual SC population shares are shown on the horizontal axis, and actual assigned seats are shown on the vertical axis. Discontinuities in the number of actual reserved seats due to rounding are visible at the vertical lines.

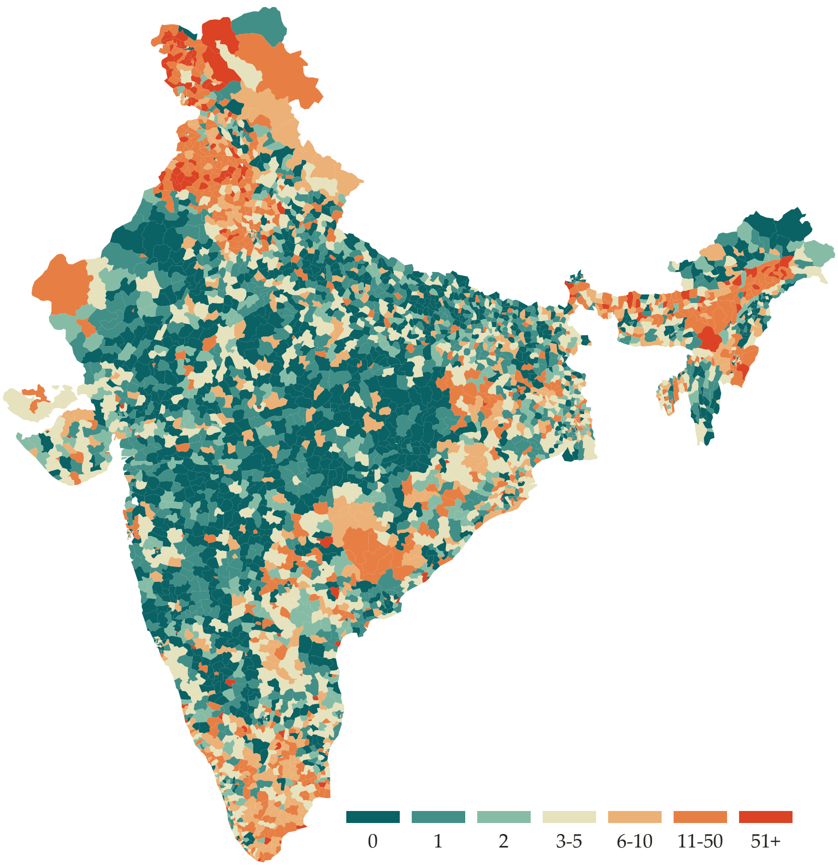
Second, I update and extend this initial conflict data. For this, I webscrape 120,000 newspaper articles on conflict-related activities collected by the South Asia Terrorism Portal between 2000 and 2024. Going back to the original data allows me to improve the measure of conflict on several dimensions: First, I extract the precise location of the events using a geocoding engine (Google Maps API), which allows me to measure outcomes at the district and the more precise constituency level. Second, I use two more advanced methods to classify events, a BERT model (Devlin et al. 2019) which I trained on ACLED data from India, and classification via a Large Language Model (OpenAI API). These allow me to describe several characteristics for each event, e.g., the number of fatalities, whether the event was related to political demands, etc. More details on the data construction are in described in Appendix B.

Other data To supplement the conflict findings, I also collected data on crimes committed against members of the scheduled castes by the National Crime Records Bureau of India. This dataset contains, for every district and year, the number of crimes committed against SCs, disaggregated by different categories in the Indian Penal system. I collect this data from 2001 to 2014.

Empirical strategy The estimate the causal effect of power-sharing through reservations I run differences-in-differences regressions at the district-year level. I estimate the following model:



(a) SC population in 2001 in %, by assembly constituency



(b) Number of conflict events, 2016-2020, by assembly constituency

Figure 5: Map: Scheduled Caste population and conflict events in India

$$\begin{aligned}\text{Conflict}_{it} = \alpha_i + \theta_t + \beta \cdot \text{Post-delimitation}_{it} \\ + \gamma \cdot \text{Post-delimitation}_{it} \times \text{Extra seats}_i + \varepsilon_{it}\end{aligned} \tag{1}$$

Conflict_{it} is a conflict outcome (count or logged number of events +1), and I use the outcomes described in the data sections in separate regressions. The model includes district fixed effects α_i and year fixed effects θ_t. $\text{Post-delimitation}_{it}$ is an indicator whether a district (in a state) has already experienced the first election after the delimitation (and thus has the new reservation allocation). Extra seats_i is a continuous variable that is the difference between actual (integer) and expected (fractional) seats of the district. The coefficient of interest, γ, is the differences-in-differences estimate of the effect of receiving an additional seat. This is a valid estimate for the causal effect of an additional reservation if the interaction of post-delimitation and extra seats is exogenous. This is plausible because receiving more or fewer reserved seats than expected is purely based on rounding, which is independent of observable and unobservable district characteristics.

Since the reserved seats are allocated to different districts at the state level, and rolled out in the next state election following the delimitation, standard errors are clustered at the state level. However, due to the small number of clusters, standard errors are unreliable. Therefore, I also present randomization inference p-values, which have the additional advantage of being robust in highly leveraged regressions (Young 2019). For this, I create hypothetical counterfactual reserved seat assignments according to the following procedure: First, I allocate seats to districts according to the delimitation rule, up to the integer part. I record the number of "leftover" seats and randomly allocate these leftover seats (without replacement) to districts within the state until no leftover seats are left. I then re-generate the extra seats variable, and re-estimate the DiD regression specification, recording the coefficient of interest. I repeat this procedure 1,000 times and report the randomization inference p-value as the share of randomized coefficients smaller than the coefficient from the actual specification.

3.2 District-level results

Table 2 presents the results from the regression for a variety of conflict outcomes from Fetzer (2020). The main result is that reservations have decreased conflict. We generally observe more conflict after the delimitation. Given the inclusion of year fixed effects, this likely captures more conflict following state elections and state government transitions. The second row of the table shows a negative interaction term across conflict outcomes. One additional reserved seat after delimitation at the district level is associated with a decrease in the total number of conflict events by around 7%, significant when considering randomization inference p-values. The effect is particularly driven by a decrease in the number of militants killed by around 6%. This gives a first indication of where conflict reduction comes from, namely from a decrease in conflict events where the government fights against military insurgents. Figure 6 shows the distribution of randomization-inference coefficients, making clear that the effect on total events and militants killed is significantly smaller than expected under reshuffling.

Table 2: District-level results: Differences-in-differences regressions

	(1)	(2)	(3)	(4)	(5)
	Total events	Killed & injured	Civilians killed	Security killed	Militants killed
After delimitation	0.099	0.077	0.059	0.065	0.053
	(0.075)	(0.081)	(0.063)	(0.046)	(0.052)
After delimitation × Extra seats	-0.066	-0.046	-0.033	-0.026	-0.062**
	(0.051)	(0.046)	(0.042)	(0.028)	(0.025)
	[0.014]	[0.285]	[0.242]	[0.276]	[0.006]
Mean of DV	1.211	1.902	0.874	0.594	0.517
Observations	7,080	7,080	7,080	7,080	7,080

Note: Differences-in-differences regression on district-year panel. Outcomes are the log of (variable+1). All specifications include district and year fixed effects. Standard errors clustered by state in parentheses. Randomization-inference p-values in brackets.

(a) DiD: Total events **(b) DiD: Security killed** **(c) DiD: Militants killed**

Figure 6: Distribution of randomization-inference DiD coefficients. x-axis shows coefficient values and y-axis shows densities. The thick black line denotes that coefficient value in the main regression, and the red histogram values show coefficients after reshuffling remaining seats across districts as outlined in the main text.

Table 3 presents results using the same sample, but the extended conflict data coded with a BERT model and a large language model. For each outcome, I estimate two BERT models and two LLM models, and I take the first principal component of the predicted values as the final predicted value. Again I estimate a reduction in total conflict events by around 6% (not significant). There is a pronounced reduction in surrenders by armed grous (by about 9%) and in violence against civilains by about 6%. section C.1 presents results on additional conflict outcomes at the district level: These are generally estimated to be sharp zeros.

To corroborate these results, I run alternative regressions where I instrument the *actual* number of reserved seats with the *rounding error*, i.e., the difference between actual and

Table 3: District-level results: Differences-in-differences regressions: BERT and LLM

	(1)	(2)	(3)	(4)	(5)
	Total events	Deaths	Surrender	Political demands	Violence vs. civil.
After delimitation	0.076	0.050	0.063	0.068	0.074
	(0.066)	(0.052)	(0.038)	(0.045)	(0.058)
After delimitation × Extra seats	-0.064	-0.013	-0.089*	-0.056	-0.060**
	(0.048)	(0.038)	(0.043)	(0.037)	(0.027)
Mean of DV	0.928	0.465	0.458	0.354	0.432
Observations	7,146	7,146	7,146	7,146	7,146

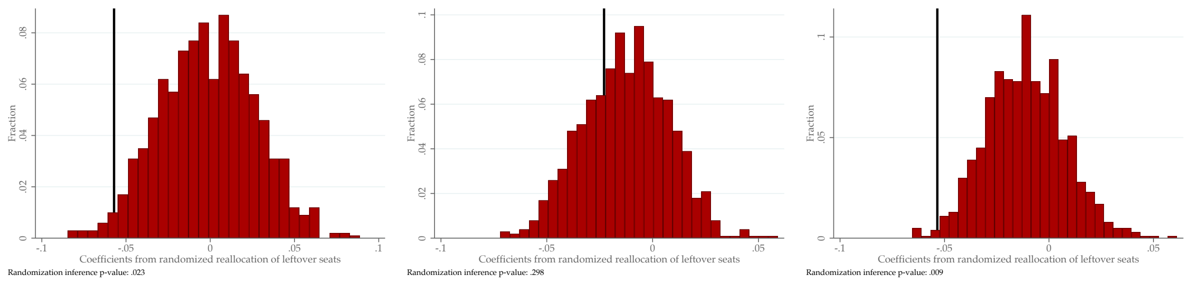
Note: Differences-in-differences regression on district-year panel. Outcomes are the log of (variable+1). All specifications include district and year fixed effects. Standard errors clustered by state in parentheses.

expected seats. This is a strong instrument, as the rounding is nearly always binding and thus mechanically affects the number of seats. For the IV estimate to have a causal interpretation, the rounding error needs to fulfill the exclusion restriction, i.e., the only way it affects conflict outcomes is via its effect on the actual number of reserved seats for scheduled castes. Again, this is a very plausible assumption, as the rounding procedure is only used to determine the precise number of reserved seats. Given these assumptions, the IV regressions estimate a local average treatment effect: the effect of one additional reserved seats for those districts that received an additonal reservation because of rounding.

Table 4: District-level results: IV-DiD regressions

	(1)	(2)	(3)	(4)	(5)
	Total events	Killed & injured	Civilians killed	Security killed	Militants killed
After delimitation	0.163***	0.122**	0.091**	0.090**	0.114***
	(0.041)	(0.055)	(0.045)	(0.037)	(0.036)
After delimitation × instr. seats	-0.057*	-0.040	-0.028	-0.023	-0.053**
	(0.031)	(0.041)	(0.034)	(0.028)	(0.027)
	[0.023]	[0.320]	[0.279]	[0.298]	[0.009]
Mean of DV	1.211	1.902	0.874	0.594	0.517
Observations	7,080	7,080	7,080	7,080	7,080
K-P F-Stat	55.8	55.8	55.8	55.8	55.8

Note: Fixed-effects IV regressions with district-year panel. Outcomes are log(outcome+1). All regressions include district and year fixed effects. The interaction of after delimitation and actual reserved seats is instrumented by the interaction of after delimitation and the rounding error (difference between actual and expected seats due to rounding). The last column reports the Kleibergen-Paap F-statistic for weak instruments in the presence of heteroskedasticity. Robust standard errors in parentheses. Significance levels: *10%,** 5%,*** 1%. Randomization inference p-values in brackets.



(a) IV: Total events **(b) IV: Security killed** **(c) IV: Militants killed**

Figure 7: Distribution of randomization-inference IV coefficients. x-axis shows coefficient values and y-axis shows densities. The thick black line denotes that coefficient value in the main regression, and the red histogram values show coefficients after reshuffling remaining seats across districts as outlined in the main text.

Table 4 presents the results from the IV regressions, with similar conflict-reducing effects. First, note that the instrument is very strong, with a Kleibergen-Paap F-statistic of more than 50. Looking at the results, we again see that the overall conflict level has been higher post-delimitation. The coefficients of interest in the second row are negative and significant throughout: One additional reserved seat after delimitation leads to a reduction by around 6% for total events and by around 5% for the number of security personnel killed. Again, randomization inference results show that the result is statistically significant (Figure 7).

To further corroborate the findings, Table 13 in the appendix estimates the local effect of an additional reservation in an RD-style regression, with qualitatively and qualitatively similar results. Using this strategy, we find once again that effects are concentrated in total events and in militants killed.

4 Constituency-level analysis

I now move on to the analysis at the state assembly constituency level. To recap, state assembly constituencies are fully contained within districts, and each assembly constituency seat receives either a reservation or not. The availability of Indian administrative data at geographic levels below the district is often spotty. For example, crimes against SCs/STs are only published at the district level. At the finer assembly constituency-level, most datasets are cross-sectional, using data from large government programs that is available at the village level but only collected once or very irregularly.

4.1 Data and empirical strategy

Reservations: I use a discrete cutoff rule from the 2008 delimitation process as a source of exogenous variation in the reservation status of an assembly constituency. For this, I gathered data from the original documents of the 2008 delimitation commission reports (Delimitation Commission of India 2008). During the 2008 delimitation process, the boundaries of India's electoral districts were redrawn, on the basis of which reserved seats were reallocated.[5] Figure 5 shows the distribution of the Scheduled Caste population, and Figure 9 the distribution of reserved seats in the state parliaments.

The delimitation commission determined the reservation of parliamentary seats by the following cutoff rule: Districts were allocated a given number of reserved seats based on the proportion of SC members relative to the whole state's proportion. Within districts, constituencies were ranked by their SC population share. Reservations were assigned starting from the highest ranked constituency, until the total number of reserved seats for the district was reached. Appendix A gives more details on this process. This rule makes it possible to compare constituencies around the cutoff to determine the effect of political reservations. In the main specification, I use the two reserved and the two unreserved constituencies closest to the cutoff. The sample definition process is explained in Figure 8, and the constituencies in the sample are shown in Figure 9, highlighting that in the vast majority of cases, reserved and unreserved constituencies in the sample are direct neighbors. [6]

By comparing the outcomes of the generated sample, a valid estimate for the (local) ef-

[5] The overall proportion of reserved seats increased only slightly, but there was substantial variation at the constituency level. For example, Haryana received the same number of total reserved seats, but

Sl. No.	No. & Name of Assembly Constituency	2001 CENSUS POPULATION TOTAL	SCs	% of SCs	SC Seats
	LUDHIANA	3032831	757962	24.99	FOUR
57	66-Gill (SC)	223528	86939	38.89	18
58	69-Raikot (SC)	192239	69482	36.14	19
59	67-Payal (SC)	200034	70966	35.48	20
60	70-Jagraon (SC)	223430	79221	35.46	21
61	68-Dakha	223652	78045	34.90	
62	57-Khanna	191398	63980	33.43	
63	58-Samrala	206400	65248	31.61	
64	59-Sahnewal	222109	68105	30.66	

Figure 8: Visualization of sample selection for the district of Ludhiana, Punjab: Having the highest proportion of SCs, constituencies 66, 69, 67, and 70 are reserved. Jagroan is the cutoff-constituency. The last two reserved constituencies (Payal and Jagroan) are added to the "treatment group". The two constituencies just below the cutoff (Dakha and Khanna) are added to the "control group".

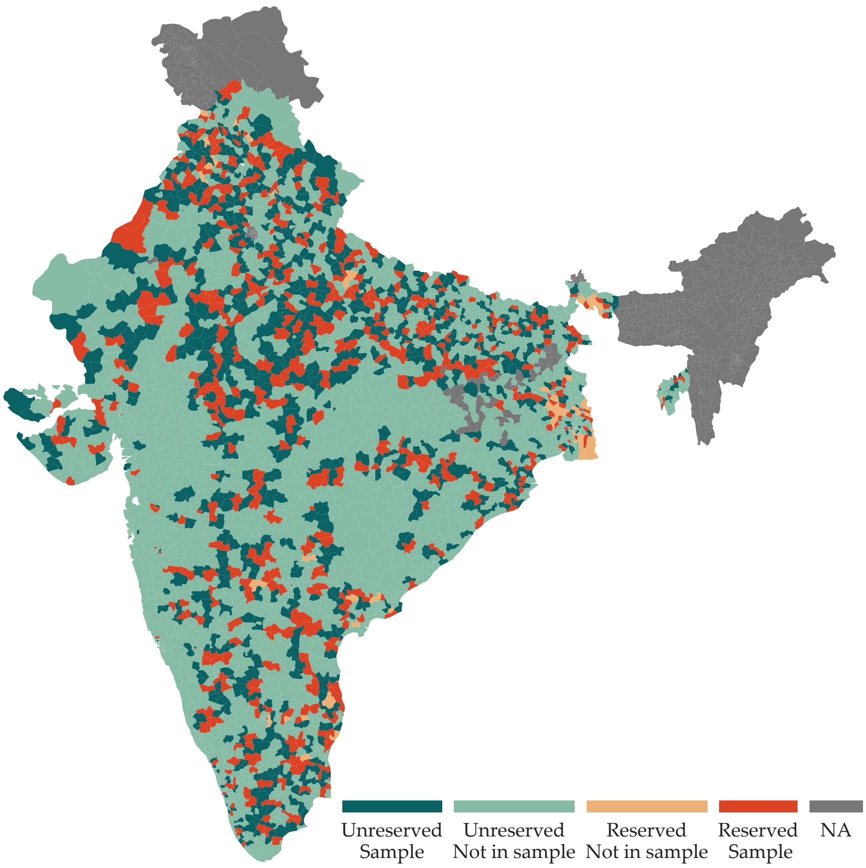


Figure 9: Map: Sample of assembly constituencies. Reservation status of assembly constituencies after the 2008 delimitation.

adjustments in the number of reserved constituencies were made for 16 out of 19 districts.

[6] In nearly all cases, the sorting of districts in the delimitation report is correct. In four out of more than

fect of reservations is obtained if the included constituencies are valid counterfactuals for each other. There are several threats to this identifying assumption. First, the delimitation process was not a random "natural experiment". The delimitation commission could have drawn the constituency boundaries according to political considerations (similar to gerrymandering). However, Iyer and Shivakumar (2009) find that the 2008 delimitation commission worked largely free of political influence and showed low levels of partisan bias. They also show that the distribution of various socio-economic outcomes was barely affected by the delimitation. Second, although the comparison of constituencies just above and below the cutoff guarantee similarity in the SC proportion, it is still possible that reserved and unreserved constituencies differ along other, potentially unobserved factors. However, Table 5 shows that the reserved and unreserved constituencies are very similar along a set of variables collected during the 2001 census. For all variables except the SC population share, a t-test of mean equality is insignificant. A Wald test of joint significance of the control variables is also insignificant.

The way the sample is generated limits the validity of the estimates to constituencies around the cutoff. Therefore, the estimate is local and findings can not be extrapolated to constituencies with very small or very large minority population shares.[7]

In a second identification strategy, I use the web-scraped and BERT-classified conflict events. Since the geocoding gives me precise coordinates of the conflict events, I can construct an assembly constituency-year panel of conflict events, and estimate differences-in-differences regressions, analyzing how conflict in just-reserved constituencies evolves compared to conflict in just-unreserved constituencies.

Conflict: There exist several datasets on political violence and subnational conflict that contain data for India.[8] However, all these are measured at the district level, and, therefore, do not allow to identify the effect at the constituency level. To overcome this, I employ two strategies: First, I use data from the Armed Conflict Location & Event Data (ACLED) Project (Raleigh et al. 2010), which codes violent conflict episodes and political process at the precise town or subdistrict area. A shortcoming of the data is that it goes back only to January 2016, which prevents me from using temporal variation in the implementation of the delimitation between 2007 and 2012. Instead, I aggregate all the conflict data from January 1, 2016 until May 30, 2020 at the constituency level. Figure 5 presents a map showing the distribution of conflict events; Figure 10 shows the distribution of fatalities. In the baseline specifications, I include all conflict

3,000 cases (districts Kottayam, Bilaspur, West Tripura and Hamirpur), the sorting had to be corrected.

[7] The comparison of the outcomes in the sample generated by this procedure is in the spirit of a regression discontinuity model with a discrete running variable, where the same limitation applies.

[8] Datasets of particular interest are the India Sub-National Problem Set (Marshall et al. 2005), the Varshney-Wilkonson Dataset on Hindu-Muslim Riots in India (Varshney and Steven. Wilkinson 2006), and Thiemo Fetzer's data on Naxalite conflict (Fetzer 2020).

data that is coded to the level corresponding to a town.[9]

Second, I use the dataset on conflict events that I webscraped, geocoded, and classified as described above and in Appendix B, giving me an assembly constituency-year panel.

Covariates: I include several variables from the 2001 Census of India in the analysis, collected from the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG), (Asher et al. 2020). While this is the most extensive available data at the constituency assembly level, one shortcoming is that not all assembly constituencies are included, reducing the potential sample size from 3,500 to 2,800. I include the proportion of the population that is member of the Scheduled Castes – this is relevant because it determines whether a constituency is reserved, and it matters for conflict in the model. I include several variables that may be related to the overall level of conflict , which will help to estimate the effect of reservations more precisely. These are the total population size, urban and rural area, and the percentage of paved roads. In addition, I include the population-normalized number of middle schools and primary schools, as well as the literacy rate, as these give information on human capital and the opportunity cost of conflict.[10] Table 5 shows summary statistics for these variables by reservation status.

4.2 Constituency-level results

Since the ACLED conflict data at the constituency level is only available after the delimitation was rolled out, I estimate cross-sectional regressions comparing reserved and unreserved constituencies in the comparison sample constructed by the cutoff-rule. I estimate regressions of the form

$$\log\left(\text{Conflict}_i + 1\right) = \alpha + \beta \text{Reserved}_i + \gamma \text{SC}_i + \mathbf{x}_\mathbf{i}'\gamma + \epsilon_i \tag{2}$$

Where "Reserved" is an indicator whether a constituency was reserved, "SC" gives the proportion of the population that belongs to the Scheduled Castes, and $\mathbf{x}$ is a vector of covariates. For the purpose of the regression models, I recoded the proportion of "SC" to have a mean of zero and a standard deviation of 1. As the model predicts that reservation is more appeasing in constituencies with larger minority populations, I expect $\beta_3 \leq 0$. I add the number 1 to the conflict variable, as many constituencies have no recorded conflict events and fatalities.

[9] I exclude some events that correspond to pure state actions, such as strategic developments. In section 5.2, I show that the main result also hold when restricting conflict to episodes that are explicitly related to castes.

[10] Unfortunately, income or consumption information, which may give additional information on opportunity costs, is not available in the 2001 census. Similarly, there is no information on economic inequality which I could use as a proxy for the parameter δ from the model.

Table 5: Balance table for assembly constituencies in the sample

Variable	(1) Runner-up (sd)	(2) Reserved (sd)	(3) Difference (p-value)
Percent SC population	20.126	24.947	4.821***
	(6.353)	(7.786)	(0.000)
Population in 1000	282.107	284.794	2.688
	(80.294)	(87.260)	(0.616)
log of Town Area in sq. km	2.786	2.736	-0.050
	(0.965)	(1.029)	(0.521)
log of Village Area in hectars	11.009	10.992	-0.017
	(1.070)	(1.057)	(0.802)
Percentage paved roads	73.652	72.822	-0.829
	(22.763)	(23.701)	(0.581)
Middle schools per 1000	0.246	0.247	0.002
	(0.160)	(0.165)	(0.864)
Primary schools per 1000	0.793	0.810	0.017
	(0.423)	(0.432)	(0.542)
Literacy rate	52.221	52.137	-0.084
	(12.129)	(11.533)	(0.913)
Wald test statistic (Jointly zero)			0.954
p-value			0.464
Observations	794	521	1,315

Note: Columns (1) and (2) report sample means and standard deviations (in parentheses). Column (3) reports the mean difference and the p-value from a t-test of mean equality (in parentheses). FThe Wald statistic and associated p-value are for a test under the null hypothesis that the regression coefficients on all variables (except the SC population share) are zero.
Significance levels: *10%,** 5%,*** 1%.

The log-linear regressions assume that the outcome variable is continuous, an assumption that is violated when using event counts. To account for this, I also estimate Poisson and negative binomial regression models as an alternative (Cameron and Trivedi 2013). While Poisson regressions are more standard,they assume equal mean and variance of the outcome, an assumption that is not supported by the data.[11] Hence, I also estimate negative binomial regression that account for this overdispersion by estimating an additional parameter governing the relation between the mean and the variance.

Table 6 presents the results for these regressions. In the OLS regressions, having a seat reserved for the SCs is associated with around 18% fewer conflict events ($\exp(-0.193) - 1 \approx -0.18$), which is significant at the 1% level. Reservations are associated with around 3% fewer fatalities from conflict, but the coefficient is not significiant. The point estimates for conflict events in the Poisson and negative binomial specifications are very similar, with reservations are associated with around 20% fewer conflict events in the preferred negative binomial specification ($\exp(-0.228) - 1 \approx -0.2$). For fatalities, the point estimates are negative, but only significant in the Poisson regressions

Table 6: Results: The effect of reservations on conflicts in constituency assemblies

	OLS ($\log X + 1$)		Poisson		Negative Binomial	
	Events	Fatalities	Events	Fatalities	Events	Fatalities
	(1)	(2)	(3)	(4)	(5)	(6)
Seat reserved for SC	−0.193***	−0.033	−0.209***	−0.392***	−0.228**	−0.272
	(0.065)	(0.026)	(0.030)	(0.124)	(0.096)	(0.188)
Percent SC population (std.)	0.229***	0.046***	0.311***	0.267***	0.267***	0.213**
	(0.032)	(0.013)	(0.013)	(0.053)	(0.047)	(0.088)
Observations	993	993	993	993	993	993
R^2	0.145	0.050				

Note: Cross-sectional regressions. All regressions include total population, schools per capita, and percent paved roads in the constituency as control variables. Significance levels: *10%, **5%, ***1%. Robust standard errors in parentheses.

Not all covariates described above are included in the main specification. However, in appendix C.2, I show that the results remain very stable when changing the combination of covariates included.

Next, it turn to differences-in-differences regressions. I again restrict the sample to the comparison sample constructed by the cutoff-rule and estimate:

$$\begin{aligned} \text{Conflict}_{it} = \alpha_i + \theta_t + \beta \cdot \text{Post-delimitation}_{it} \\ + \gamma \cdot \text{Post-delimitation}_{it} \times \text{Reserved}_i + \varepsilon_{it} \end{aligned} \tag{3}$$

[11] In the baseline sample, the mean of the number of events is 4.3 and the variance is 88.7, for fatalities, the values are 0.3 and 1.1, respectively.

Instead of the extra reserved seats at the district level, I can directly compare reserved to unreserved constituencies before and after delimitation. I control for district (i.e., constituency pair) and year fixed effects, and cluster standard errors at the level at which reservations are allocated, i.e., at the district level. Results are shown in Table 7. In contrast to previous regressions, I find no significant impact of reservations on conflict at the assembly level when using the BERT-coded data.

Table 7: Constituency-level results: DiD regressions

	(1)	(2)	(3)	(4)	(5)
	Total events	Deaths	Surrender	Political demands	Violence vs. civil.
After delimitation	0.005	0.007	0.001	0.006	0.005
	(0.007)	(0.006)	(0.004)	(0.005)	(0.005)
After delimitation × Reserved	0.000	0.008*	-0.003	0.003	-0.000
	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)
Mean of DV	0.082	0.043	0.043	0.031	0.035
Observations	29,179	29,179	29,179	29,179	29,179

Note: DiD regression on district-year panel. Outcomes are the log of (variable+1). All specifications include district (i.e., constituency-pair) and year fixed effects. Standard errors clustered by district in parentheses.

4.3 Summary of main results

The results both paint an encouraging picture of the effect of political reservations on conflict: Across a wide variety of outcomes, reservations have reduced low-level subnational conflict in India. The estimates from district- and assembly-level regressions can be seen as complimentary: The constituency-level regressions answer *where* exactly the conflict reductions are coming from – precisely from the constituencies that just made the cutoff and received a reservation. The district-level results are more coarse, but take into account larger trends and spillovers within the district. Therefore, the reduction of conflict at the district-level shows that reservations at the constituency-level do not merely *displace* conflict, but reduce the aggreate level of conflict (at the district level). This also speaks to the backlash-hypothesis: the appeasing effect at the assembly level outweighs any backlash at the district-level (i.e., in non-reserved constituencies), leading to an aggregate reduction in conflict.

An important limitation of this argument is that I am only able to take into account spillover effects at the district level, so I am unable to consider trends in conflict induced by reservations that are uniform across states or the whole country.

5 Mechanisms

This section investigates the drivers behind the reduction in conflict caused by political reservations.

5.1 Reduction in crimes

Table 8 presents results from district-level regressions with the logged number of crimes against members of the Scheduled castes as outcome. Mirroring the effects on conflict outcomes, one extra reserved seat after delimitation is associated with a reduction in total crimes against scheduled castes by close to 20%. Disaggregating crimes into different penal categories (crimes according to the 1989 Protection of Atrocities Act, the 1955 Protection of Civil Rights Act, other crimes, and murder) shows that there is no systematic heterogeneity in the estimates. It is particularly interesting to note that the coefficient on murders committed against lower castes is small and significant: While there may be systematic under-reporting across other categories, it is very difficult to conceal murder, which increases confidence that these findings represent actual decreases in crime.

This suggests that the observed reduction in conflict may not only stem from a decline in low-level violence involving reserved groups, but also from a decrease in crimes committed against members of the lower castes. Accordingly, the crime results provide additional evidence against the backlash hypothesis – that unreserved groups responded to reservations with increased violence toward SC communities.

Table 8: District-level crime results: Differences-in-differences Poisson regressions

	(1)	(2)	(3)	(4)	(5)
	Total crimes	POA	PCR	Other crimes	Murder
After delimitation	-0.161***	-0.091	0.661**	-0.311***	0.188***
	(0.039)	(0.084)	(0.317)	(0.073)	(0.064)
After delimitation × Extra seats	-0.192*	-0.215	-0.224	-0.369**	-0.300**
	(0.112)	(0.234)	(0.566)	(0.186)	(0.138)
Mean of DV	65.222	21.780	1.561	29.172	1.532
Observations	5,931	5,347	2,060	5,340	5,247
Pseudo R^2	0.735	0.588	0.605	0.706	0.393

Note: **Note:** Fixed-effects Poisson regressions with district-year panel. POA and PCR crimes are crimes according to the Protection of Atrocities Act (1989) and the Protection of Civil Rights Act (1955), respectively. All regressions include district and year fixed effects and control for the interaction between after delimitation and expected fractional reserved seats. Robust standard errors in parentheses. Significance levels: *10%,** 5%,*** 1%

5.2 Reduction in caste-related low-level conflict

To closer investigate the types of conflict affected by reservations, I restrict the set of conflict events to those mentioning caste-based categories.[12] This filter therefore proxies the intensity of conflict related to communal tensions related to caste. Applying this filter reduces the number of conflict events from 59,996 to 3,428. As there are only 213 associated fatalities, I only report results on conflict events.

Table 9 shows results from log-linear OLS, negative binomial, and Poisson regressions when using only these 3,428 caste-related conflict events from the ACLED data. Throughout all specifications, reservations are associated with fewer conflict events in the unconditional model (significant at the 10% level, and at the 1% level for Poisson regressions). As an important limitation, the analysis has much lower power than the main analysis because the number of events included is reduced significantly.

Table 9: Caste-related conflict events only

	OLS (log $Y+1$)		Poisson		Negative Binomial	
	(1)	(2)	(3)	(4)	(5)	(6)
Seat reserved for SC	-0.056*	-0.076**	-0.450**	-0.496**	-0.331**	-0.450**
	(0.029)	(0.035)	(0.184)	(0.214)	(0.168)	(0.218)
Perc. SC pop (std.)	0.029	0.118*	0.248*	0.776*	0.156	0.721*
	(0.021)	(0.070)	(0.137)	(0.397)	(0.113)	(0.380)
Mean of DV	0.43	0.44	0.43	1.04	0.43	0.43
Observations	993	941	993	396	993	993
R-squared	0.069	0.568				
District FE + cluster SE		✓		✓		✓

Note: Cross-sectional constituency-level regressions. Regression only uses events related to caste by filtering for events with at least one of the keywords `caste`, `jati`, `schedule`, `" sc "`, `(sc)`, `obc`, `discrim`, `reserv`, `dalit`, `forward`, `untouch`, `brahmin`, `jaat`. All regressions include total population, schools per capita, and percent paved roads in the constituency as control variables. Even-numbered columns include district fixed effects and have standard errors clustered at district level. Significance levels: *10%, **5%, ***1%.

5.3 Naxalites

The district-level results showed that the reduction in conflict has been particularly pronounced for conflict deaths of militants. This suggests that the effect of political representation of scheduled castes may be driven by a reduction of relatively high-level conflict between the government and organized militants. The main organized militant insurgency group in India is the Maoist-Naxalite insurgency that is active across states in North India.

[12] The full list of strings I use for filtering is: `caste`, `schedule`, `brahmin`, `untouch`, `forward`, `obc`, `dalit`, `reserv`, `jat`, `jaat`, `" sc "`, `(sc)`, `discrim`, `category`.

Analyzing the Naxalite conflict in particular is especially relevant to the research question: The Naxalite rebellion specifically targeted lower-caste and tribal communities, and systematically appealed to their existing grievances in efforts to recruit members (Scanlon 2018). Therefore, analyzing whether reservations were particularly effective in reducing conflict in Naxalite areas, where conflict because of minority grievances is rampant, provides a direct test of the mechanism proposed in the paper.

To investigate this, I collect information on the number of Naxalite-related conflict events by district up to 2008 (prior to delimitation). I define this as "Naxalite intensity". I then first run the district-year DiD-regressions and interact the variables of interest with intensity of the Naxalite rebellion in a district. Second, I can run the constituency-level regressions, interacting the presence of a reserved seat Naxalite intensity.

Table 10 and Table 11 show the results of this exercise. There is some heterogeneity across estimates. However, most coefficients on the interaction terms are significant and negative: This indicates that reserved seats were more effective in reducing conflict in areas in which the Naxalite rebellion was active prior to delimitation. The finding also shows that the observed conflict reduction is not only driven by low-level conflict, but also by reductions in fatalities in areas with violent insurgent activity.

Table 10: District-level regression: Naxalites

	(1)	(2)	(3)	(4)	(5)
	Total events	Killed & injured	Civilians killed	Security killed	Militants killed
After delimitation	0.096***	0.075**	0.060**	0.061***	0.052***
	(0.022)	(0.030)	(0.025)	(0.020)	(0.020)
After × Extra seats	-0.063*	-0.043	-0.035	-0.022	-0.060*
	(0.036)	(0.048)	(0.039)	(0.032)	(0.031)
After × Naxalite intensity	-0.007	-0.011	0.014*	-0.016***	-0.004
	(0.007)	(0.009)	(0.007)	(0.006)	(0.006)
After × Extra × Naxal	-0.104*	-0.151*	0.125*	-0.211***	-0.052
	(0.060)	(0.080)	(0.066)	(0.053)	(0.052)
Mean of DV	1.211	1.902	0.874	0.594	0.517
Observations	7,080	7,080	7,080	7,080	7,080

Note: Differences-in-differences regression on district-year panel. All specifications include district and year fixed effects. Standard errors clustered by state in parentheses.

Table 11: Constituency-level regression: Naxalites

	OLS ($\log X + 1$)		Poisson		Negative Binomial	
	Events (1)	Fatalities (2)	Events (3)	Fatalities (4)	Events (5)	Fatalities (6)
Share SCs	0.036***	0.010***	0.041***	0.039***	0.040***	0.036***
	(0.005)	(0.002)	(0.002)	(0.005)	(0.006)	(0.010)
Reserved seat	-0.178**	-0.013	-0.332***	-0.126	-0.297***	-0.001
	(0.081)	(0.040)	(0.036)	(0.138)	(0.115)	(0.204)
Naxalite state	0.363***	0.222***	0.305***	1.047***	0.462***	1.093***
	(0.092)	(0.046)	(0.038)	(0.121)	(0.134)	(0.227)
Reserved seat × Naxalite state	-0.097	-0.110	0.162***	-0.566***	0.061	-0.723**
	(0.135)	(0.067)	(0.056)	(0.177)	(0.190)	(0.316)
Mean of DV	5.789	0.593	5.789	0.593	5.789	0.593
Observations	993	993	993	993	993	993

Note: Regressions for constituency cross-section. All regressions include the following constituency-level controls: total population, schools per capita, and percent paved roads. Robust standard errors clustered at state level in parentheses. Significance levels: *10%,** 5%,*** 1%

6 Conclusion

This paper adds to the recent literature on heterogenous and unintended consequences of political reservation by providing a detailed analysis of the effects of political reservations on subnational conflict. I showed that more reservations at the district level had led to a reduction in conflict. Conflict is also lower in reserved compared to similar unreserved constituencies over the last four years. I provided evidence on low-level conflict and crimes against SCs that there is no measureable backlash by unreserved groups that is detectable in conflict or crime statistics. The conflict reduction is broad, but particularly concentrated when looking at fatalities of security personnel and militants, mirrored by higher conflict reductions in constituencies in Naxalite areas.

While this analysis has shown that local reservations have appeasing effects even at a larger scale – providing evidence against large conflict spillover effects – the frame of reference of this paper is still local. Therefore, I am unable to capture state- or national-wide effects, such as potential effects of pro-minority legislation passed by reserved MLAs in the state-parliaments. Another feature of my identification strategy is that the estimates are local treatment effects valid for districts that just received one additional reserved seats, and for constitutiencies just at the cutoff. While I have found encouraging results at this policy-relevant margin, extrapolating the results in order to infer policy recommendations for more reservations is not possible.

A task for future research is to analyze how reservations affect perpetrator-victim relations and the types of conflict episodes. Hence, this paper gives some evidence on the appeasing effect of permanent reservations, but also opens up a new set of puzzles to be explored by future research. Another active and exciting area of research is the large spatial persistence of conflict. One possibility to account for this would be to estimate spatial regression models. The rich interaction between constituency- and district-level analysis in this paper can be naturally extended to estimate the spatial effects of additional reservations, which would provide further insight into the general-equilibrium effects of mandated political representation.

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A Description of constituency data merging process

During the delimitation process, the allocation of reserved seats was determined by the following procedure:

1. For every state, the proportion of reserved seats in the state parliament is determined as the (rounded) proportion of the SC population within the state.
2. Within each state, the seats are allocated by district. The SC population in a district divided by the total SC population in a state, multiplied by the total number of reserved seats in a state gives the total number of reserved seats within a district, up to rounding. For example, a district with 5% of the total SC population of a state would be entitled to receive 5% of the reserved seats for that state.
3. Within each district, assembly constituencies are ranked by their SC population share. Counting down from the constituency with the highest proportion of SCs, all constituencies receive reservation until the total number of reserved seats is reached.

Community Created Maps of India 2020 supplied shapefiles for the assembly constituencies. Several manual corrections were performed:

1. Several assemblies were missing from the maps. Some urban constituencies (in Gandhinagar, Ahmedabad, Surat, Indore) were missing because of an error in the original source. This was manually corrected using maps from Wikipedia and georeferencing in Q-GIS.
2. The shapefiles included sea areas and areas not in the control of India in the Northwest and Northeast, which I dropped for the analysis.
3. Non-unique assembly names were renamed to facilitate merging.
4. Some small errors in the naming of constituencies were corrected.

The data extracted from the Delimitations Commissions Reports was merged with the Spatial Data using a fuzzy merge on a string containing the Assembly Constituency names and the name of the state. The spatial data was then merged to the SHRUG assembly data.

Conflict data from ACLED is available with geocoding, it was merged to the Shapefile using a spatial merge function in R that sums all observations within a spatial polygon, i.e. within an assembly constituency. In the baseline specifications, I exclude the following event types: "Government regains territory", "Strategic Developments", "Shelling/artillery/missile attack". Figure 10 maps the resulting distribution of conflict fatalities across assembly constituencies.

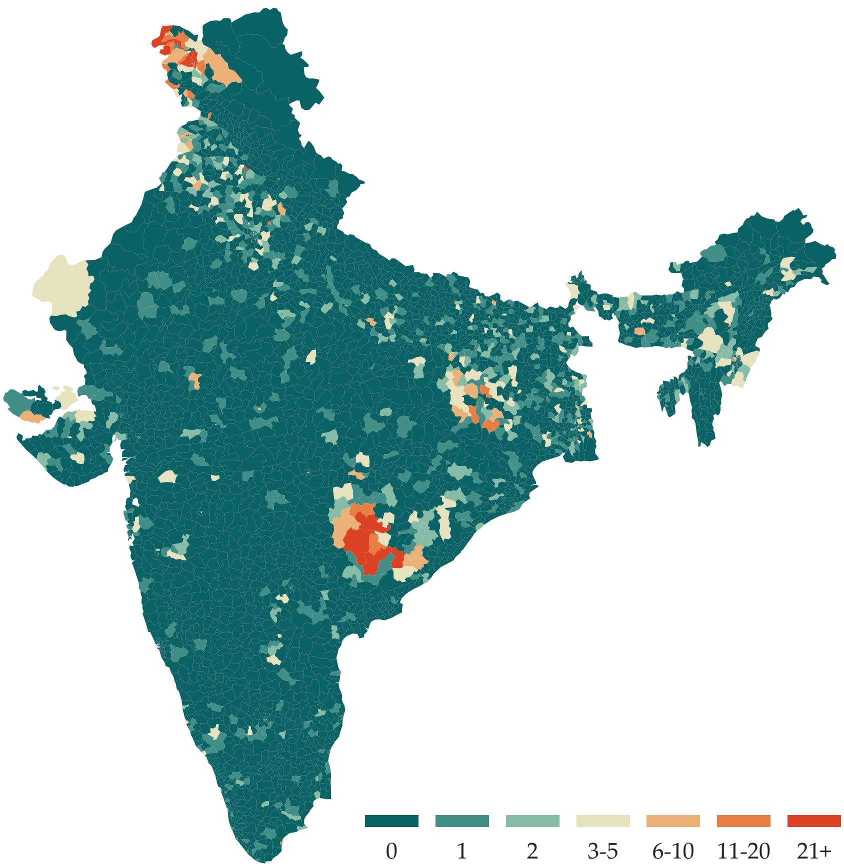


Figure 10: Map: Number of fatalities from conflict, 2016-2020, by assembly constituency.

B Description of conflict event coding

To build district-year and assembly-constituency-year panels of conflict events, I proceed in several steps.

1. **Webscraping**: I webscrape a total of 121,453 events from the South Asia Terrorism Portal (SATP) at https://www.satp.org/terrorist-activity/india.
2. **Address Standardization**: I use the OpenAI API and the gpt-4.1-mini-2025-04-14 model to transform event description to standardized address strings.
3. **Google Maps API Geocoding**: Each unique location description is geocoded using the Google Maps Geocoding API, which returns latitude and longitude coordinates, and information on the precision of the location description (the size of the viewport, i.e. the zoom window used in a Google Maps result
4. **Filtering**: I filter geocoded results to exclude events outside of India and events with insufficient precision. Starting from 120,146 unique scraped events:
   - Excluded 64 events without a location description (120,082 events remaining)
   - Excluded 11,883 events with generic state-level or country-level locations (108,199 remaining)
   - Excluded 6,994 events whose location descriptions reference foreign countries or could not be geocoded (101,205 remaining)
   - Excluded 10,567 events with imprecise geocodes (viewport spans exceeding 100 kilometers) or locations outside India's boundaries (distance > 2,634 km from geographic center)

   The final dataset contains 90,638 geocoded conflict events. For the regression analysis, I further restrict this sample to precisely geocoded events (viewport spans of at most 20 kilometers; 73,024 events) and drop events that both LLMs classify as not describing a concrete conflict event (72,650 remaining), events with inconsistent multi-location coding (69,900 remaining), and events that both LLMs classify as purely external border conflicts. The analysis sample contains 63,896 events.
5. **BERT Classification of Conflict Events** BERT (Bidirectional Encoder Representations from Transformers) is a machine learning model that converts text into numerical representations by analyzing words in context from both directions simultaneously, allowing it to understand the meaning of words based on their surrounding context (see Devlin et al. (2019) for a technical introduction into BERT models). For conflict event coding, BERT is suitable because it can be trained to classify text descriptions into predefined categories, and fine-tuned on domain-specific data. BERT models have been used in empirical economics, for example by Giaccherini and Kopinska (2023).

   I employ two BERT model variants: The largest available BERT model (`bert_en_cased_L-12_H-768_A-12`) and the smallest available BERT model (`bert_en_uncased_L-2_H-128_A-2`). The BERT model has to be trained on a training dataset. I train on two separate datasets. First, a sample of 1 million conflict events drawn from the worldwide ACLED data (Armed Conflict Location & Event Data Project; 2.6 million events, 1997–2025): I keep all events from South Asia and fill the remainder with events from other world regions, allocated in equal numbers across the six ACLED event types so that rarer categories are well represented in training. Second, a subset of ACLED using all events from India and a random sample of 10,000 events from other South Asian countries (Pakistan, Nepal, Bangladesh, and Sri Lanka). I truncate text descriptions to 10,000 characters maximum, and use the ACLED conflict categories: riots, protests, strategic developments, violence against civilians, explosions, and battles, alongside the number of fatalities. (ACLED does not record injury counts; injuries are coded only by the LLM models described below.) The BERT model is trained to predict, for each conflict event, whether or not that event is a riot, a protest, etc. I use class weights to handle imbalanced categories. For fatalities, I train the same architectures as a regression on the ACLED fatality count. Estimating each combination of model size and training sample separately yields four BERT-based predictions per category.

The BERT models were fine-tuned for 5 epochs with the AdamW optimizer, with a learning rate of 3e-5 with linear warmup schedule. The output of the BERT models is a probability score for each conflict category on the unlabeled SATP dataset, producing continuous measures between 0 and 1.

6. **LLM models**: I classify each event description with two large language models, gpt-5-mini and gpt-5-nano (OpenAI), accessed through the Batch API using the open-source GABRIEL library.[13] Each model performs two tasks: a *classification* task that assigns 17 binary labels, and an *extraction* task that returns the integer number of fatalities and of non-fatal injuries reported in the text. The binary labels and their definitions are:

```
1 RELEVANT  The text describes a concrete conflict or crime event (attack, battle,
arrest, riot, protest, seizure, surrender, etc.)  that occurred at a specific place
and time.  Speeches, policy statements, analyses, statistics, or summaries of many
incidents are NOT concrete events.
2 MULTI     The text reports events at two or more distinct places, or on two or more
distinct dates.
3 INT       The event concerns internal conflict within India, including foreign militants
caught or operating inside India.  Incidents occurring purely across the border (cross-frontier
shelling, clashes with another country's troops on the border) are NOT internal.
4 SURRENDER Any party voluntarily surrenders, receives amnesty, or is appeased.
5 ECON      The dispute centres on economic grievances, development, or the distribution
of resources.
6 POLITICS  The dispute centres on political demands, laws, ideology, separatism,
or politicians.
7 COMMUNITY The dispute is between social, religious, or ethnic communities.
8 CASTE     Caste issues are substantively involved in the event:  violence or discrimination
against Dalits / Scheduled Castes / OBCs, inter-caste conflict, or caste-based reservations
as the subject of the dispute.  A mere mention of a person's caste is NOT sufficient.
9 MAOIST    The event is linked to Naxalite / Maoist organisations.
```

[13] openai-gabriel, https://pypi.org/project/openai-gabriel/. The library constructs the prompts from explicit label definitions, enforces structured responses, and parses them into one column per label.

```
10 ORGCRIME The activity is organised crime: smuggling, drugs, fake currency (FICN),
gold, arms trafficking, extortion rackets, and similar.
11 VIOLENT  Physical violence occurred: any injury, death, or use of force.
12 RIOT     The event is a riot: a violent demonstration or mob violence by an unorganised
crowd.
13 PROTEST  The event is a protest: a public demonstration in which participants
do not engage in violence, though they may be met with violence.
14 BATTLE   The event is a battle: an armed clash or exchange of fire between two
organised armed groups (militants, security forces).
15 EXPLOSION The event involves a bomb, IED, grenade, landmine, shelling, or another
explosive or stand-off weapon.
16 VAC       The event is violence against civilians: an organised armed group deliberately
attacking unarmed civilians (killings, abductions, assaults).
17 STRATDEV The event is a strategic development: a non-violent action by a conflict
actor, such as arrests, seizures, agreements, recruitment, troop movements, or the
establishment of bases.
```

Labels 12–17 are event types and an event can satisfy more than one; they replicate the ACLED event-type definitions, so that every conflict category classified by the BERT models is also coded by both LLMs. In the count-extraction task the models are instructed to return 0 when no number is stated; responses of "unknown" or similar are likewise coded as 0, consistent with that rule. Extreme count values (above 200 in a single event) are set to missing and cross-checked manually; these are almost always monetary or aggregate figures from the headline that the model misplaced in the casualty field.

7. **Data Aggregation:** I clean and aggregate the data: Large fatality estimates are manually cross-checked. I drop irrelevant events (these are, for example, descriptions of strategic developments, speeches by politicians related to terrorism, etc.) For each of the six ACLED event categories and for the number of fatalities, I have six separate estimates: four BERT predictions (two model sizes, each trained on the worldwide and on the South Asian sample) and two LLM predictions. The remaining categories are coded only by the LLMs, giving two estimates each. I aggregate the estimates for each category by extracting the first principal component of the standardized measures and rescaling it to the unit interval: negative values are set to zero and, except for the fatality and injury counts, values above one are set to one. Negative values arise mechanically because the principal component is centered at zero; they correspond to events for which all underlying measures indicate the absence of the category, and setting them to zero restores that interpretation. Figure 11 shows the correlation across the different measures at the event level. Figure 12 and Figure 13 show the corresponding correlations after summing the measures to the district and constituency-year levels at which the regressions are estimated. Agreement across measures increases with aggregation, as idiosyncratic classification error averages out: the mean within-category correlation rises from 0.58 at the event level to 0.95 at the district level and 0.86 at the constituency-year level.

8. **Panel dataset construction:** I create the annual panel dataset by spatially intersecting (point-in-polygon) the longitude/latitude values from from conflict event dataset with district boundaries (from the Global Administrative Atlas, GADM) and constituency boundaries. I aggregate events to the boundary-year

level by summing all conflict measures within each boundary-year cell. Missing boundary-years are filled with zeros.

Validation against human coding. To validate the automated classifications against human judgment, a team of five trained coders (research assistants and the author) independently hand-coded a random sample of 800 SATP event descriptions using the same coding scheme. 524 of these events were coded by at least two coders, which allows me to measure inter-coder agreement — the ceiling that any automated method can realistically attain, since it reflects the intrinsic ambiguity of the event descriptions. Human labels are aggregated by majority vote across coders (events with an exact tie are dropped for the affected label), and casualty counts by the coder mean; 609 of the hand-coded events fall inside the final geocoded dataset. Table 12 reports the results.

For the casualty counts — the measures used most directly in the analysis — the LLM coding is statistically indistinguishable from human coding: both models correlate at $r = 0.98$–0.99 with the hand-coded fatality and injury counts, with a mean absolute error of about 0.1, compared with an inter-coder correlation of 0.97 between the human coders themselves. Among the BERT fatality models, the small model trained on the worldwide sample tracks the human counts reasonably well (rank correlation $\rho = 0.71$) despite never having seen SATP data or Indian fatality counts during training; the remaining BERT fatality variants correlate only weakly with the human counts, consistent with their low cross-measure correlations in Figure 11. This is one motivation for aggregating several measures per category rather than relying on any single model.

For the binary classifications, accuracy against the human majority vote ranges from 0.62 to 0.99. Agreement is highest exactly where the category is well-defined: for surrender events, caste conflict, and Naxalite/Maoist involvement, the better LLM (gpt-5-mini) reaches Cohen's κ of 0.77–0.89, close to the human-human benchmark of 0.71–0.93. Agreement is lower for intrinsically judgment-laden motive attributions (political demands, communal framing) and for the internal-conflict flag, where the models apply a narrower definition of "internal conflict" than the human coders, who classified 92 percent of events as internal. Because the analysis-sample filter drops an event only when *both* LLMs agree it is irrelevant, non-internal, or inconsistently coded, disagreement on these gray-zone labels translates into a more conservative (larger) analysis sample rather than into misclassification of retained events.

Table 12: Automated conflict coding compared with human coders. Panel A benchmarks the binary LLM classifications against the majority vote of up to five human coders on 800 hand-coded SATP events (609 of which fall in the geocoded sample); "Human coders" columns report pairwise agreement and Cohen's κ between human coders on the 524 double-coded events. Panel B benchmarks the fatality and injury counts; r and ρ are the Pearson and Spearman correlations with the hand-coded counts and MAE is the mean absolute error.

			GPT-5-mini		GPT-5-nano		Human coders	
Measure	N	Prev.	Acc.	κ	Acc.	κ	Agr.	κ
Panel A: Binary classifications								
Relevant event	603	0.76	0.81	0.32	0.77	0.10	0.92	0.82
Multiple events	524	0.09	0.88	0.28	0.85	0.37	0.95	0.70
Internal conflict	529	0.92	0.63	0.04	0.76	-0.00	0.93	0.50
Pacification/surrender	531	0.09	0.97	0.77	0.97	0.77	0.99	0.93
Economic conditions	531	0.04	0.97	0.55	0.97	0.37	0.98	0.73
Political demands	520	0.11	0.62	0.19	0.67	0.19	0.91	0.67
Communal conflict	527	0.02	0.85	0.12	0.91	0.05	0.97	0.65
Caste conflict	531	0.02	0.99	0.80	0.98	0.39	0.99	0.71
Naxalite/Maoist	521	0.25	0.96	0.89	0.85	0.66	0.95	0.89
Organized crime	528	0.05	0.88	0.35	0.89	0.35	0.97	0.76

Panel B: Casualty counts (vs. human coding, values capped at 200)

Measure	Model	N	Human mean	Model mean	r	ρ	MAE
Fatalities	GPT-5-mini	530	0.83	0.82	0.98	0.94	0.11
Fatalities	GPT-5-nano	519	0.84	0.81	0.98	0.91	0.13
Fatalities	BERT-base (India)	530	0.83	0.14	-0.03	-0.01	0.92
Fatalities	BERT-small (India)	530	0.83	0.24	-0.01	0.07	0.94
Fatalities	BERT-base (world)	530	0.83	1.77	0.00	0.10	2.29
Fatalities	BERT-small (world)	530	0.83	0.61	0.64	0.71	0.68
Fatalities	Human coder pairs	–	–	–	0.97	–	0.06
Injuries	GPT-5-mini	530	1.20	1.13	0.99	0.95	0.12
Injuries	GPT-5-nano	519	1.22	1.13	0.99	0.93	0.13
Injuries	Human coder pairs	–	–	–	1.00	–	0.02

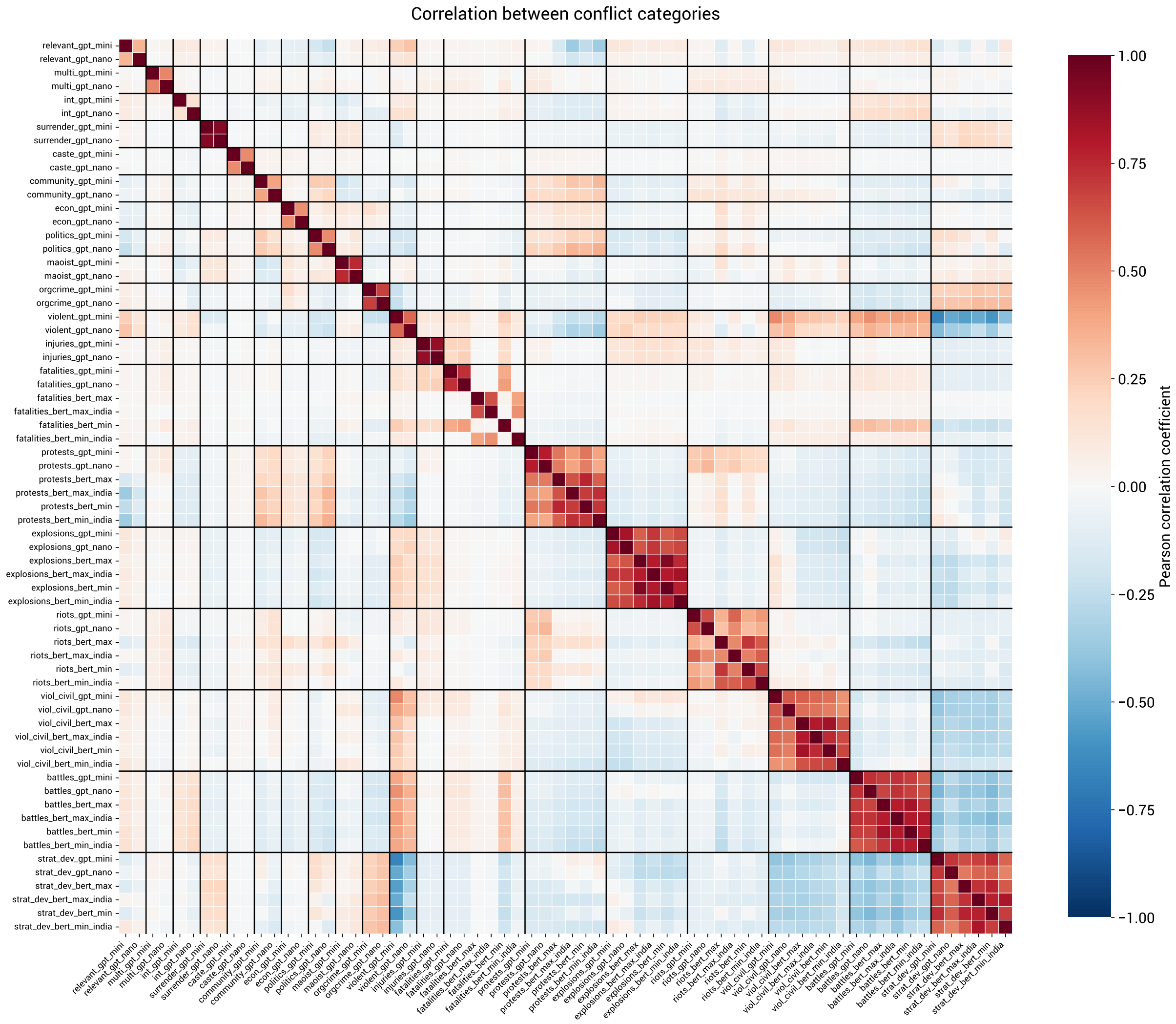


Figure 11: Correlation between conflict measures from the four BERT models and the two GPT-5 LLM models, by conflict category. Pearson correlations computed at the event level across the 90,638 geocoded SATP conflict events.

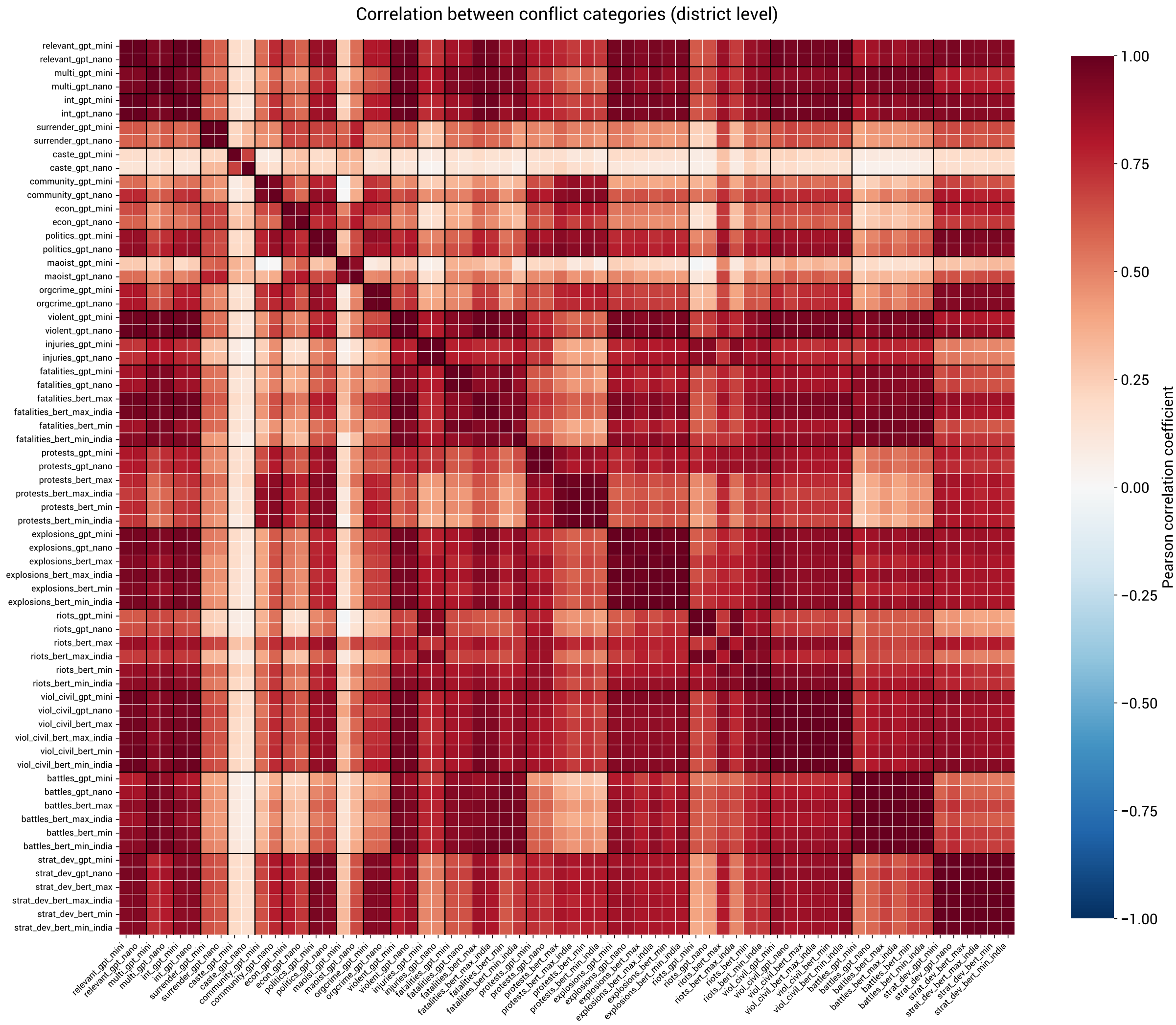


Figure 12: Correlation between conflict measures, aggregated to the district level. Each measure is summed within district across the analysis sample of 63,630 events (576 GADM districts).

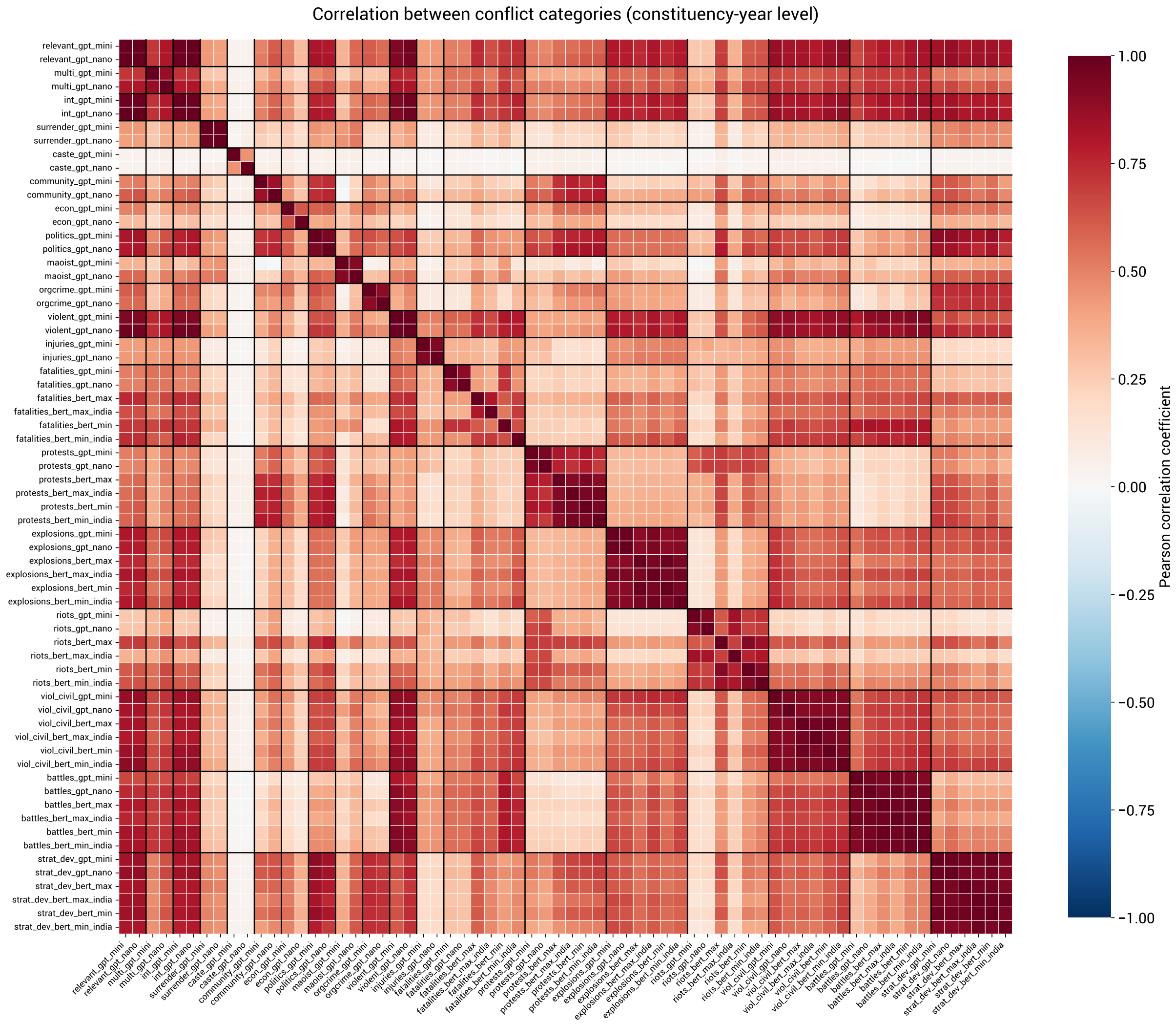


Figure 13: Correlation between conflict measures, aggregated to the constituency-year level. Each measure is summed within assembly-constituency-year cells with at least one event in the analysis sample (14,139 cells across 2,330 constituencies).

C Robustness Checks

C.1 Districts

As alternative to the Poisson and IV regressions in the main text, I estimate a regression discontinuity-type specification, where I recenter the rounding error so that it can be used as a running variable. The coefficient of interest is the coefficient on the interaction of post-delimitation and an indicator variable that the running variable is greater than zero. This estimates the local effect of receiving an additional reserved seat by rounding. The regressions control for the interaction between after delimitation and the running variable, as well as for the interaction between after delimitation and the expected fractional seats.

Table 13: District-level results: Regression discontinuity regressions

	(1)	(2)	(3)	(4)	(5)
	Total events	Killed & injured	Civilians killed	Security killed	Militants killed
After delimitation	0.255***	0.266***	0.180***	0.167***	0.213***
	(0.069)	(0.074)	(0.057)	(0.045)	(0.053)
After delimitation $\times$ running variable>0	-0.070	-0.063	-0.053	-0.043	-0.105*
	(0.096)	(0.090)	(0.065)	(0.055)	(0.057)
Mean of DV	1.213	1.906	0.876	0.595	0.518
Observations	7,065	7,065	7,065	7,065	7,065
Within R-squared	0.016	0.012	0.007	0.009	0.014

Note: Fixed-effects RD-style regressions with district-year panel. All regressions include district and year fixed effects. The running variable is the rounding error recentered so that it ranges between -0.5 and 0.5 that is zero at fractional seats 0.5, 1.5, 2.5, etc. All regressions control for the interaction between after delimitation and the running variable, as well as for the interaction between after delimitation and the expected fractional seats. Robust standard errors in parentheses. Significance levels: *10%,** 5%,*** 1%

Table 14 shows differences-in-differences results for additional conflict outcomes coded via BERT/LLM models.

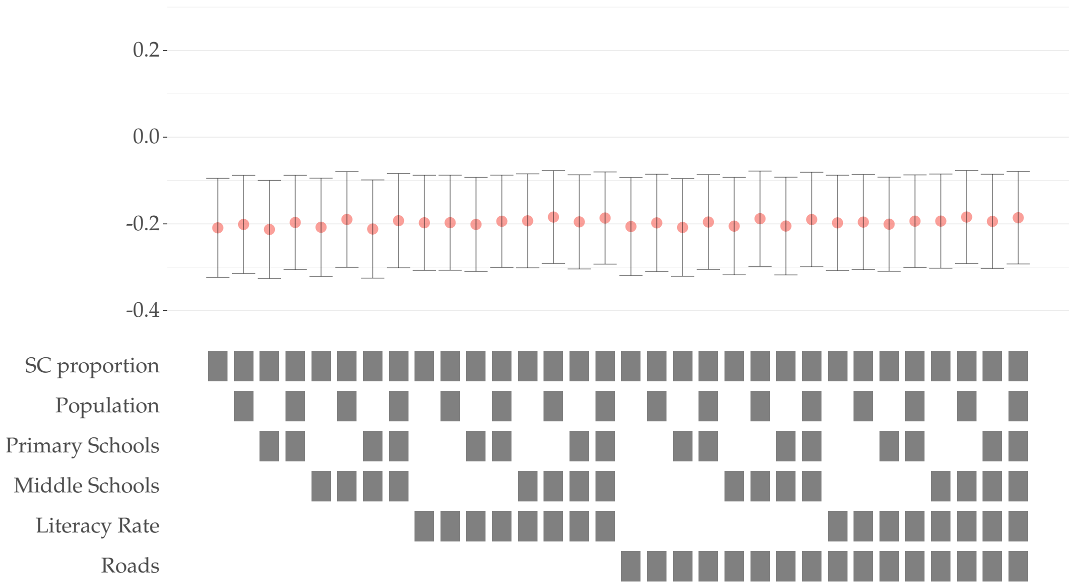
Table 14: District-level results: Differences-in-differences regressions: BERT

	(1)	(2)	(3)	(4)	(5)
	Econ. griev.	Maoist events	Protests	Riots	Caste related
After delimitation	0.018	0.061	0.016	0.049	0.002
	(0.030)	(0.068)	(0.013)	(0.043)	(0.004)
After delimitation × Extra seats	-0.005	-0.044	-0.001	-0.020	-0.012
	(0.019)	(0.047)	(0.011)	(0.021)	(0.012)
Mean of DV	0.125	1.089	0.062	0.323	0.017
Observations	7,146	7,146	7,146	7,146	7,146

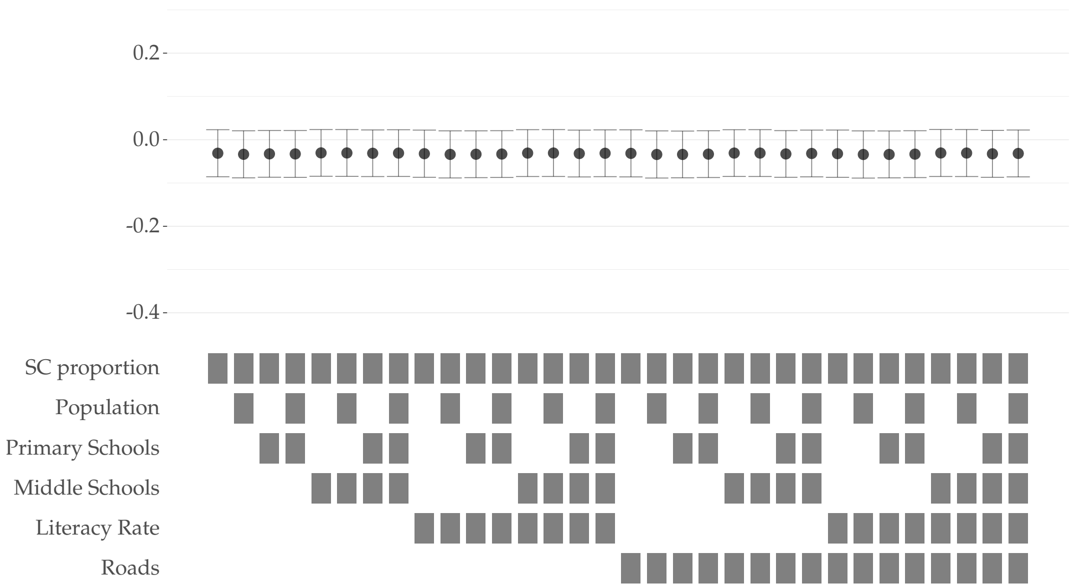
Note: Differences-in-differences regression on district-year panel. Outcomes are the log of (variable+1). All specifications include district and year fixed effects. Standard errors clustered by state in parentheses.

C.2 Constituencies

To show that the results of the log-linear OLS specification are robust to the inclusion of different combinations of covariates, Figure 14 plots estimated coefficients and 95% confidence intervals for all possible combinations of covariates. I always include the proportion of SC as a control variable. All other covariates are permuted, to show all possible combinations. The results remain very stable throughout the exercise.



(a) Robustness checks for events



(b) Robustness checks for fatalities

Figure 14: Robustness of coefficient on conflict in linear models

Note: Regression of log(variable + 1) on reservation and a permutated set of covariates, for sample of assembly constituencies. Standard errors clustered by district. Red dots denote p-values below 0.01. Green: p<0.05. Blue: p<0.1. Black: p>0.1.

D A simple model of political reservations

To motivate why reservations can reduce conflict even if they create more losers than winners, I present a simple static model that relates public goods provision to ethnic conflict. Ethnic groups have different income endowments and policy preferences. Individuals derive utility from a public good that is targetable and provided by a politician. The core assumption is that poorer individuals react more sensitively to changes in public goods provison. While politicians take dissatisfaction and conflict into account when choosing their policy, they are also ideological. Therefore, when the minority is large and poorer than the majority, reserving a political position for the minority would generate less overall dissatisfaction, and therefore less conflict than a status quo policy.

The model resembles the citizen-candidate model with reservations in Chattopadhyay and Duflo (2004). However, while their results rely on differences in the cost of running for office and elite capture, the driving channel in this model is the difference in groups' propensity to engage in conflict.

D.1 Assumptions

There are two groups $i = \{A, B\}$, where A denotes the minority (i.e., SCs) and B the majority (Forward Castes). The population is normalized to unit mass, with shares s and $1 - s$ for minority and majority, respectively. [14] As with the case of SCs in India, the minority is poorer; income endowments for the groups are y_A and y_B, such that $0 \leq y_A < y_B < 1$. Let δ denote the absolute income gap, and $y_B = y_A + \delta$.

Individuals' utility: Individuals derive utility from a public good and private exogenous income, such that individual i's utility function is:

$$U_i(x_i, y_i) = y_i - (1 - y_i) \cdot (x - x_i)^2 \tag{4}$$

The first term denotes utility derived from exogenous private income y_i. Income enters linearly, capturing constant marginal utility from consumption.[15]

The second term denotes utility from a public good x. While Alesina et al. (1999) allow for group-specific types and quantities of a public good and Besley, Pande, et al. (2004) model group-specific public goods with spillovers, I assume – for simplicity – that a single public good $x \in [0, 1]$ is provided. Groups have different preferred x_i, such that $x_A > x_B$. In this exposition, I interpret this as differences in the preferred *quantity* of the public good. However, Interpretations as the geographical distance to the public good or other notions of a *targetable* public good are equally valid.[16] Utility from the public good is quadratically decreasing in the distance to the preferred policy, and moderated by income y_i. Specifically, individuals with higher income are

[14] It would be possible to assume that s < 1/2, but this assumption is not required for the solution of the model.

[15] The results do not rely on the function form of this additively separable term.

[16] See Alesina et al. (1999) for a general model of targeted public goods, and Anderson et al. (2015) and Munshi and Rosenzweig (2018) for implications of this targetability.

less affected by deviations from their preferred level of the public good, for example because they can more easily substitute away from the public good than poorer individuals, or because richer households have a distaste for public goods. [17]

Decision to engage in conflict I abstract from strategic aspects in the decision to engage in conflict. Instead, conflict arises from the dissatisfaction of individuals with the implemented policy: Individuals become sufficiently dissatisfied to engage in conflict if their utility drops below a stochastic individual-specific threshold, which is uniformly distributed over $[-\gamma, \gamma]$, with $\gamma \geq 1/2$.[18] γ, therefore, reflects the degree of heterogeneity in the thresholds. As the utility is directly linked to an individual's propensity to engage in conflict, the more sensible reaction of poorer individuals to deviations from their preferred policy can also be interpreted as lower economic opportunity cost of engaging in conflict.

For interior solutions, the mass of individuals engaging in conflict is:

$$n = s \cdot \left[\frac{\gamma - U_A(x_A, y_A)}{2\gamma}\right] + (1-s) \cdot \left[\frac{\gamma - U_B(x_B, y_B)}{2\gamma}\right] \tag{5}$$

$$= \frac{1}{2} + \frac{1}{2\gamma} \cdot \left[\alpha \cdot (x - x_A)^2 + \beta \cdot (x - x_B)^2 - (y_A + (1-s)\delta)\right] \tag{6}$$

, where $\alpha = s(1 - y_A)$ and $\beta = (1-s)(1 - y_A - \delta)$.

D.2 Conflict minimization

Consider a social planner who implements the "efficient" policy x^* to minimize aggregate dissatisfaction, and hence, conflict. As conflict is a convex function of x, the first order condition for an interior solution is necessary and sufficient:

$$\left.\frac{\partial n}{\partial x}\right|_{x=x^*} = 0 \quad \Leftrightarrow \quad x^* = \frac{\alpha}{\alpha+\beta} x_A + \frac{\beta}{\alpha+\beta} x_B \tag{7}$$

The social planner chooses a weighted sum of the preferred policies, where the weights depend on the population shares and the difference in incomes. A larger population share of the minority and a larger absolute income gap increase the weight on the minority policy.

Denoting $\Delta x = x_A - x_B$ (the distance between the preferred policies), the minimized level of conflict is:

$$n^* = \frac{1}{2} + \frac{1}{2\gamma} \left(\frac{\alpha\beta}{\alpha+\beta} (\Delta x)^2 - y_A + (1-s)\delta\right) \tag{8}$$

$\gamma \geq 1/2$ guarantees that the level of conflict remains below one.[19] The case where income is so high that no one engages in conflict is ignored.

[17] In the Indian context, this has a very direct additional interpretation: the distaste for public goods could come from a preference against sharing public resources with people from lower castes, prescribed by still existant social norms such as untouchability.

[18] This assumption ensures that the mass of individuals in conflict reacts continuously to policy changes. $\gamma \geq 1/2$ ensures that the marginal effect of policy changes is not too large, which would lead to discontinuities and corner solutions for some parameter values.

[19] $\frac{\alpha\beta}{\alpha+\beta}$ is never larger than $1/4$, and the policy difference never larger than one.

D.3 Political process

Several assumptions allow me to simplify the political process: First, I assume that politicians are directly recruited from either population group and are ideological; they have the same preference for the public good as their ethnic group.[20] Second, I assume that under an open election, the politician in power is always from the majority, while under a reserved election, the politician is from the minority. This is a strong but not unrealistic assumption (see Besley, Pande, et al. 2004; Bhavnani 2017). Third, politicians cannot commit to policies before an election. Together with the second assumption, this allows me to ignore the election process and instead focus on the incentives incumbents face. The only choice parameter for politicians is the level of the public good provided.

Politicians in office have reelection incentives:[21] When reelected, politicians receive a continuation payoff b, otherwise a payoff of c, with $1 > b - c := \chi \geq 0$. The probability of reelection π is directly related to the utility of citizens and simply corresponds to the mass of 'satisfied' citizens, i.e. $\pi = 1 - n$. We can write the politician's utility function as:

$$V_i(x_i) = \pi b + (1 - \pi) \cdot c - (x - x_i)^2 \tag{9}$$

$$= b - \chi \cdot \left[\frac{1}{2} + \frac{1}{2\gamma} \cdot \left(\alpha \cdot (x^* - x_A)^2 + \beta \cdot (x^* - x_B)^2\right) - \frac{y_A + (1-s)\delta}{2\gamma}\right] - (x - x_i)^2 \tag{10}$$

D.4 Reelection constraints and permanent reservations

In India, the seats for the parliamentary assembly (on the national level) and for constituency assemblies (on the state level) are *permanently* reserved: Politicians are free to run for reelection, creating incentives to implement more equitable policies in order to increase reelection prospects.

Open elections We continue to require that a majority politician gets elected. She maximizes $V_B(x_B)$. The solution to this maximization problem is

$$x^O_{re-el} = \frac{2\gamma + \beta\chi}{2\gamma + (\alpha + \beta)\chi} \cdot x_B + \frac{\alpha\chi}{2\gamma + (\alpha + \beta)\chi} \cdot x_A \tag{11}$$

$$= \frac{2\gamma + \beta\chi}{\kappa} \cdot x_B + \frac{\alpha\chi}{\kappa} \cdot x_A \tag{12}$$

where, for notational purposes, $\kappa = 2\gamma + (\alpha + \beta)\chi$. The policy is a weighted sum of the preferred policies of both groups. Since the politician is from the majority, she places a larger weight on x_B than the social planner.[22] Larger income differences and a larger minority population make it more costly to implement majority policies and bring the policy implemented by the majority politician closer to the minority's position.

[20] Therefore, the model is in the spirit of a citizen-candidate model, such as Osborne and Slivinski (1996) and Besley and Coate (1997), but it ignores the selection of candidates.

[21] In a similar spirit, Bardhan and Mookherjee (2010) present a model that nests the cases of purely ideological and purely opportunistic politicians.

[22] This is because $2\gamma \geq 1 \geq \alpha\chi$.

The realized public good determines the level of conflict:

$$n^O_{re-el} = \frac{1}{2} + \frac{1}{2\gamma} \cdot \left[\alpha \cdot \left(\frac{2\gamma + \beta\chi}{\kappa} \right)^2 + \beta \left(\frac{\alpha\chi}{\kappa} \right)^2 \right] (\Delta x)^2 - \frac{y_A + (1-s)\delta}{2\gamma} \tag{13}$$

Reserved elections By definition, a minority politician gets elected. The solution to her maximization problem is

$$x^R_{perm} = \frac{2\gamma + \alpha\chi}{\kappa} \cdot x_A + \frac{\beta\chi}{\kappa} \cdot x_B \tag{14}$$

The level of conflict under permanent political reservation is then

$$n^R_{perm} = \frac{1}{2} + \frac{1}{2\gamma} \cdot \left[\alpha \cdot \left(\frac{\beta\chi}{\kappa} \right)^2 + \beta \left(\frac{2\gamma + \alpha\chi}{\kappa} \right)^2 \right] (\Delta x)^2 - \frac{y_A + (1-s)\delta}{2\gamma} \tag{15}$$

Two insights follow from the previous results:

Proposition 1. *The policy implemented by a minority politician is always closer to the preferred minority policy x_A than the policy implemented by a majority politician, as $x^R_{perm} - x^O_{perm} = \frac{2\gamma}{\kappa} \cdot (\Delta x) > 0$.*

Proposition 2. *As long as the implemented policies are not too extreme, the effect of political reservations is more appeasing with larger minority shares and larger income inequality.*[23]

Proof. Reservation increases the quantity of the public good provided. We can hence determine the sign of the effect by using Equation 7.

$$\begin{aligned} \frac{\partial \frac{\partial n}{\partial x}}{\partial s} &= (1 - y_A)(x - x_A) - (1 - y_A - \delta)(x - x_B) && (16) \\ &= \delta(x - x_B) - (1 - y_A)(\Delta x) && (17) \end{aligned}$$

As $x \in [x_B, x_A]$, the expression is negative.

$$\frac{\partial \frac{\partial n}{\partial x}}{\partial \delta} = -(1-s)(x - x_B) \tag{18}$$

Assuming again that $x \in [x_B, x_A]$, the expression is negative, and zero only when the policy preferred by the majority is implemented. □

Assembly elections: In national and state-level assemblies, reservations are permanent, so that both majority and minority candidates face reelection constraints. In this scenario, the difference in conflict between reserved and unreserved is:

$$\begin{aligned} n^R_{perm} - n^O_{re-el} &= \frac{(\Delta x)^2}{2\gamma\kappa^2} \left[\alpha(\beta\chi)^2 + \beta(2\gamma + \alpha\chi)^2 - \alpha(2\gamma + \beta\chi)^2 - \beta(\alpha\chi)^2 \right] && (19) \\ &= \frac{(\Delta x)^2}{2\gamma\kappa^2} (\beta - \alpha) && (20) \end{aligned}$$

[23] This proposition can be empirically verified by determining the sign of the interaction term between minority share and political reservation.

The linear utility term is independent of the policy and drops out. Since the first factor is positive, the sign is uniquely determined by $\beta - \alpha = (1-s)(1-y_A-\delta) - s(1-y_A)$.

Proposition 3. *Given a sufficiently high minority share and income gap, we will have $\alpha > \beta$. In that case, conflict in permanently reserved constituencies is below conflict in open constituencies.*[24]

D.5 Conclusion and Limitations

The model provides a simple conceptual framework relating the effect of mandated minority representation on conflict to relative population size and sensitivity to engage in conflict. The framework is of course very simple and abstracts from several empirically relevant channels: We largely abstract from the microeconomic decision to engage in conflict, which is typically modelled as strategic decision, such as in Besley and Persson (2011) and Mitra and Ray (2014). An interesting avenue for further exploration would be to acknowleddge that the provision of public goods must be financed via taxes raised from citizens (see, e.g., Lindbeck and Weibull 1987). In this scenario, raising the level of the public good will introduce an additional effect via increased taxation.

[24] In the framework without reelection incentives, the policy implemented by the minority politician generally leads to lower conflict than the policy implemented by the majority politician if $\alpha > \beta$.