# Mandated Political Representation and Low-Level Conflict: Evidence from India

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**Abstract**

This paper analyzes the effect of political reservations on low-level subnational conflict in India. The recent literature on the impact of reservations on public goods provison finds that reservations benefit the targeted minorities. This may come at the detriment of other minorities or forward castes. I explore the latter possibility in a simple formal model of targeted public goods provision. The model indicates that reservations reduce conflict the larger and economically more disadvantaged the targeted minority is. However, this result may be mediated by reelection incentives. I investigate the predictions of the model with empirical data from Indian constituencies and village-level surveys. At the constituency level, where politicians can be reelected, reservations are associated with significantly lower levels of conflict. At the village level, the rotation of reservations constitutes an implicit term limit, and reservation is, if at all, associated with more conflict.

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# 1 Introduction

The topic of mandated political representation – reserving political office such as seats in the parliament for historically disadvantages minorities – has been one of the most contested topics in Indian politics over the last decades: Attempts to extend the scope of reservations of led to large-scale violent protests, such as when the influential report of the Mandal commission recommended reserving of public sector jobs and extending reservation rights to Other Backward Classes in 1990. Communities engage in public rebellion to demand their inclusion in one of the reserved categories, as members of the North Indian *Jat* community did in 2016, when their 10 day protest to be included in the OBC category disrupted public services across several Indian states and caused at least 30 fatalities (Times of India 2016; NDTV India 2016). Finally, the reservation policy has also spurred horrific inter-caste violence: In 1996, following the election of an SC member for a reserved *pradhan* seat in Melavalavu, Tamil Nadu, members of higher castes murdered the *pradhan* and five other *dalits* (Narula 1999; Acemoglu and Robinson 2019).

These important anecdotes suggest that political reservations are related to political protest, civil unrest, and communal violence, which are all different facets of low-level conflict.[1] While the abovementioned accounts suggest that reservations have increased societal tensions, an argument often brought forward in favor of mandating better political representation for minorities is that this leads to more equitable political and economic outcomes, thus reducing structural causes of conflict. It is therefore an open question how political reservations affect low-level conflict, and what mechanisms drive the relation between the two. This paper presents the first analysis of the relation between reservations and low-level conflict. For this, I study the example of political reservations for Scheduled Castes (SCs), a historically disadvantaged group that is one of the primary targets of affirmative action in India.

My analysis is motivated by a theoretical framework has a simple thought as starting point: the relation between reservations and overall conflict is potentially ambiguous and will depend on the relative size of the winners and losers from reservation, and by their relative sensitivity to engage in conflict. I attempt to formalize this idea in a model of targeted public goods provision. The minority is poorer and has lower opportunity cost of engaging in conflict. Therefore, the main result of the model is that policies closer to the minority position may improve overall satisfaction and reduce conflict if the minority population and inter-group income differences are sufficiently large. However, in the absence of reelection incentives, minority politicians will implement too extreme policies, potentially reverting the result.

To empirically verify the predictions of the model, I use data from assembly constituen-

[1] For the purpose of this paper, I define conflict very broadly to include events of political violence as well as political protests. Therefore, both the satisfaction of citizens with the political system and inter-group conflict dynamics are potentially captured by the analysis.

cies, where reserved politicians can be reelected, and survey data from Indian villages, where a rotation system in combination with established norms often prevents the reelection of minority politicians. I exploit two sources of exogeneity to estimate the local effect of reservations: First, I consider the reallocation of reserved seats for the state parliaments in 2008, where a discrete cutoff rule on the assembly constituency (state parliament) level allows me to compare the outcomes of very similar constituencies with or without reservation. Second, I use survey data on the village level, where the chief political position, the *pradhan*, is reserved based on a rotational system. In contrast to the examples given above, the empirical analysis shows that reservations are *not* associated with more conflict. Instead, reservations have a significant negative effect on conflict intensity on the assembly constituency level. This result remains robust in various specifications, and also when considering only caste-related conflict. The relation between reservation and conflict is less clear at the village level, but I can rule out large positive or negative effects. The empirical results are consistent with the theoretical model and the result that reservations reduce conflict when coupled with reelection incentives.

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 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 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 electoral quotas, which have become an increasingly popular instrument to improve the political representation of minorities. Today, more than 100 countries use such quotas 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, notably the provision of public goods (Pande 2003, Chattopadhyay and Duflo 2004, Besley et al. 2004, Dunning and Nilekani 2013), poverty (Chin and Prakash 2011), 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 et al. 2012) as well as redistribution at the expense of the majority population (Sharan and Kumar 2019b). 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; 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, 2004; Miguel et al. 2004; Dube and Vargas 2013, for Hindu-Muslim riots Bohlken and Sergenti 2010, for the Naxalite conflict (Vanden Eynde 2018; Fetzer 2020). Most of these studies 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.

Finally, this paper is grounded in a long and distinguished political economy literature on reelection incentives (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 GP-level did not have sizeable redistributive effects because of the presence of multi-ethnic parties and dynamic incentives of politicians. I build on this literature and add the insight that the effect of mandated representation may differ depending on whether the reservation system makes it possible for reserved politicians to run for reelection. This is a central bolt in my model, and explains the different effects of reservations on the village and constituency level.

The rest of the paper is organized as follows: section 2 gives a brief overview of the political reservation system in India and the main institutions analysed in this study. Section 3 introduces a formal model of conflict and public goods allocation that gives some predictions on the relation between reservations, reelection incentives, and conflict. Section 4 presents the data and identification strategy, and section 5 presents and discusses the empirical results. Section 6 concludes.

## 2 Affirmative Action 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* (individuals 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 affirmative action 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 affirmative action, 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 make up 16.6% and 8.6% of the population, respectively, less than three percent of all non-reserved seats in legislative assemblies are won by SC/ST candidates, as shown in Table 1.

**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 |

To overcome these disparities, India has implemented so-called *political reservations* on all levels of political decision making. Such reservations are currently implemented for SCs, STs and women. If a political position is reserved for a specific group, only members of this group can run as candidates, while these candidates are still being elected by the general voting population. 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 percent, reflecting their relative increase in the population share. The assignment of constituencies to a reservations status is permanent and changes only when constituency boundaries are redrawn in a delimitation process; the last two such delimitations were implemented in 1974 and 2008.

On the local level, political reservations have been mandated by the Constitution since 1992. The lowest level of political organization in India is the *Gram panchayat* (GP), a local council typically representing around 10,000 citizens in several villages (Chattopadhyay and Duflo 2004). The position of the chief executive at the local level, the *pradhan*, is subject to a *rotational* reservation for SCs, STs, and women. This system guarantees that the seat of the *pradhan* is never reserved for the same group twice in a row.

Both on the local and on the state level, there is ample evidence that the reserved positions are politically and economically important, indicating that politicians on reserved seats have the power to to influence political and economic outcomes and also conflict beyond a mere symbolic effect of minority representation: The federal structure of India 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. However, activities for their constituency are even more important than their legislative work (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 at least some 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).

*Pradhans* head the GPs and are the chief executives at the local level. While the exact responsibilities of the GPs are set by the state, they perform a range of typical tasks (Besley et al. 2004): Firstly, they select beneficiaries for welfare schemes. Secondly, they provide and maintain local public goods and infrastructure, such as drinking water and roads. Decisions in the council are taken by majority voting but there is substantial evidence that the *pradhan* has the *de facto* capacity to influence and target policies (Chattopadhyay and Duflo 2004; Besley et al. 2004). For example, Dutta et al. (2014) note that the *pradhan* has a key role in implementing MGNREGA, a large public employment guarantee programme and Dunning and Nilekani (2013) discribe how the *pradhan* often serves as intermediary between citizens and higher-level administration.

Finally, both MLAs and Pradhans are typically elected for five years, giving them substantial time to influence policy outcomes.

[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.

# 3 Model

In the following section, I present a 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. There also exists a range of parameter values for which permanent reservation reduces conflict compared to status quo, wheras rotating reservation, which asymetrically affects reelection incentives, increases conflict.

The model resembles the citizen-candidate model with reservation 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.

## 3.1 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. [3] 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 $\delta$ 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:

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

The first term denotes utility derived from exogenous private income $y_i$. Income enters linearly, capturing constant marginal utility from consumption.[4]

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 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

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

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

$x_A > x_B$. 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.[5] 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 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.[6]

**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. Following Rößler et al. (2019), this happens if their utility drops below a stochastic individual-specific threshold, which is uniformly distributed over $[-\gamma, \gamma]$, with $\gamma \geq 1/2$.[7] $\gamma$, 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:

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

$$= \frac{1}{2} + \frac{1}{2\gamma} \cdot \left[\alpha \cdot (x - x_A)^2 + \beta \cdot (x - x_B)^2 - (y_A + (1-s)\delta)\right] \tag{3}$$

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

## 3.2 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:

$$\left.\frac{\partial n}{\partial x}\right|_{x=x^*} = 0 \quad \Leftrightarrow \quad x^* = \frac{\alpha}{\alpha+\beta} x_A + \frac{\beta}{\alpha+\beta} x_B \tag{4}$$

[5] 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.

[6] 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.

[7] 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.

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:

$$n^* = \frac{1}{2} + \frac{1}{2\gamma}\left(\frac{\alpha\beta}{\alpha+\beta}(\Delta x)^2 - y_A + (1-s)\delta\right) \tag{5}$$

$\gamma \geq 1/2$ guarantees that the level of conflict remains below one.[8] The case where income is so high that no one engages in conflict is ignored.

### 3.3 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.[9] 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 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:[10] When reelected, politicians receive a continuation payoff $b$, otherwise a payoff of $c$, with $1 > b - c := \chi \geq 0$. The probability of reelection $\pi$ 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:

$$V_i(x_i) = \pi b + (1-\pi)\cdot c - (x - x_i)^2 \tag{6}$$

$$= b - \chi \cdot \left[\frac{1}{2} + \frac{1}{2\gamma}\cdot\left(\alpha\cdot(x^* - x_A)^2 + \beta\cdot(x^* - x_B)^2\right) - \frac{y_A + (1-s)\delta}{2\gamma}\right] - (x - x_i)^2 \tag{7}$$

8 $\frac{\alpha\beta}{\alpha+\beta}$ is never larger than $1/4$, and the policy difference never larger than one.

9 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.

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

## 3.4 No reelection constraints and rotational reservations

First consider the case where politicians in office are not reelected, i.e. $b = c$ or $\pi = 0$. In the case of rotating reservations, such as for *Gram panchayats*, this term limit might be implicit and asymmetric: *Pradhans* on reserved seats will not run for office again as the following open election will anyways be won by a majority candidate. However, *pradhans* on unreserved seats will usually be able to contest again, unless their seat becomes reserved.[11]

From the utility function, we directly see that politicians without reelection prospects implement their preferred policy: $x = x_i$. Following the assumptions, under open elections (superscript $O$), a majority politician gets elected, yielding $x^O_{nre-el} = x_B$ and the associated conflict:

$$n^O_{nre-el} = \frac{1}{2} + \frac{1}{2\gamma} \cdot \left[\alpha \cdot (x^O_{nre-el} - x_A)^2 + \beta \cdot (x^O_{nre-el} - x_B)^2 - (y_A + (1-s)\delta)\right] \tag{8}$$

$$= \frac{1}{2} + \frac{1}{2\gamma} \cdot \alpha \cdot (\Delta x)^2 - \frac{y_A + (1-s)\delta}{2\gamma} \tag{9}$$

Under (rotationally) reserved elections (superscript $R$), a minority politician gets elected, yielding $x_{rot} = x_A$ and the associated conflict:

$$n^R_{rot} = \frac{1}{2} + \frac{1}{2\gamma} \cdot \beta \cdot (\Delta x)^2 - \frac{y_A + (1-s)\delta}{2\gamma} \tag{10}$$

## 3.5 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

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

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

[11] Chattopadhyay and Duflo (2004) find that there is no difference in policy outcomes between *pradhans* with or without reelection constraints. They explain this with the fact that many *pradhans* initially did not understand the consequences of rotating reservation. Contrary to this, several studies show the empirical relevance of reelection constraints, e.g. Besley and Case (1995), Ferraz and Finan (2011), and Parthasarathy (2017).

larger weight on $x_B$ than the social planner.[12] 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.

The realized public good determines the level of conflict:

$$n^O_{re-el} = \frac{1}{2} + \frac{1}{2\gamma} \cdot \left[ \alpha \cdot \left( \frac{2\gamma + \beta\chi}{\kappa} \right)^2 + \beta \left( \frac{\alpha\chi}{\kappa} \right)^2 \right] (\Delta x)^2 - \frac{y_A + (1-s)\delta}{2\gamma} \tag{12}$$

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

$$x^R_{perm} = \frac{2\gamma + \alpha\chi}{\kappa} \cdot x_A + \frac{\beta\chi}{\kappa} \cdot x_B \tag{13}$$

The level of conflict under permanent political reservation is then

$$n^R_{perm} = \frac{1}{2} + \frac{1}{2\gamma} \cdot \left[ \alpha \cdot \left( \frac{\beta\chi}{\kappa} \right)^2 + \beta \left( \frac{2\gamma + \alpha\chi}{\kappa} \right)^2 \right] (\Delta x)^2 - \frac{y_A + (1-s)\delta}{2\gamma} \tag{14}$$

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.** [13] *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.*[14]

## 3.6 Comparing outcomes

**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:

$$n^R_{perm} - n^O_{re-el} = \frac{(\Delta x)^2}{2\gamma\kappa^2}(\beta - \alpha) \tag{15}$$

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

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

[13] See appendix A1.1 for proof.

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

**Proposition 3.** *Given a sufficiently high minority share and income gap, $\alpha > \beta$, and conflict in permanently reserved constituencies is below conflict in open constituencies.*[15]

**Panchayat elections:** For GPs, the difference in conflict between reserved and unreserved is driven by the different reelection incentives the incumbents will face. Reserved candidates are by assumption not able to run for reelection, while a candidate elected in an open election may run again.[16]

$$n^R_{rot} - n^O_{re-el} = \frac{(\Delta x)^2}{2\gamma\kappa^2} \cdot \left[2\beta^2\chi^2(2\gamma + \alpha) + (\beta - \alpha)(4\gamma^2 + \beta^2\chi^2)\right] \tag{16}$$

**Proposition 4.** [17] *There exists a range of paramter values such that the following holds: Conflict under **rotational reservation** exceeds conflict under open election, even when conflict under **permanent reservation** is lower than under open elections, as long as the minority share and the income gap are not too large.*

Intuitively, larger minority shares and inequality make minority representation more desirable. On the other hand, if the minority politician does not face reelection constraints, she implements extreme policies. Unless the share of the minority and the inequality are very high, this extreme policy leads to an over-provision of public goods relative to the majority policy under reelection incentives.

## 3.7 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.

[15] 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 $\alpha > \beta$.

[16] There is still the possibility that a previously open seat may be reserved in the next election. However, I assume that no reserved politician will be reelected again, while this is only true for some openly elected candidates. Hence, this will attenuate the results without changing them qualitatively.

[17] See appendix A1.2 for proof.

# 4 Data and identification strategy

Simply comparing the outcomes of reserved and unreserved constituencies (or GPs) 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 also associated with more conflict. To overcome this selection bias, I use plausibly exogenous variation in reservations on both political levels included in the analysis.

## 4.1 Constituencies

**Reservations:** Similar to Natraj (2011), 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.[18] Figure 2 shows the distribution of the Scheduled Caste population and 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 A4 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 1, and the constituencies in the sample are shown in Figure 2, highlighting that in the vast majority of cases, reserved and unreserved constituencies in the sample are direct neighbors.[19] [20]

By comparing the outcomes of the generated sample, a valid estimate for the (local) effect of reservations is obtained if the included constituencies are valid counterfactuals for each other. There are several threats to this identifiying assumption. First, the delimitation process was not a random "natural experiment". The delimitation commission could have drawn the constitueny boundaries according to political con-

[18] The overall proportion of reserved seats increased only slightly, but there was substantial variation at the constituency level. For example, the 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.

[19] In appendix A2.1.2, I also present results including all districts above and below the cutoff within a 5 percentage point margin of the SC population.

[20] In nearly all cases, the sorting of districts in the delimitation report is correct. In four out of more than 3,000 cases (districts Kottayam, Bilaspur, West Tripura and Hamirpur), the sorting had to be corrected.

| No. & Name of Assembly Constituency | 2001 CENSUS POPULATION TOTAL | SCs | % of SCs | SC Seats |
|---|---|---|---|---|
| GURDASPUR | 2103455 | 520548 | 24.75 | THREE |
| 2-Bhoa (SC) | 204805 | 87004 | 42.48 | 1 |
| 5-Dina Nagar (SC) | 220034 | 71122 | 32.32 | 2 |
| 8-Sri Hargobindpur (SC) | 202313 | 56892 | 28.12 | 3 |
| 1-Sujanpur | 215307 | 57508 | 26.71 | |
| 9-Fatehgarh Churian | 198369 | 50938 | 25.68 | |
| 7-Batala | 223223 | 51504 | 23.07 | |

**Figure 1:** Visualization of sample selection for the district of Gurdaspur, Punjab: Having the highest proportion of SCs, constituencies 2, 5, and 8 are reserved. Sri Hargobindpur is the cutoff-constituency. The last two reserved constituencies (Dina Nagar and Sri Hargobindpur) are added to the "treatment group". The two constituencies just below the cutoff (Sujanpur and Fatehgarh Churian) are added to the "control group".

siderations (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 2a 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.[21]

**Conflict:** There exist several datasets on political violence and subnational conflict that contain data for India.[22] However, all these are measured at the district level, and, therefore, do not allow to identify the effect at the constituency level. I therefore 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

[21] 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.

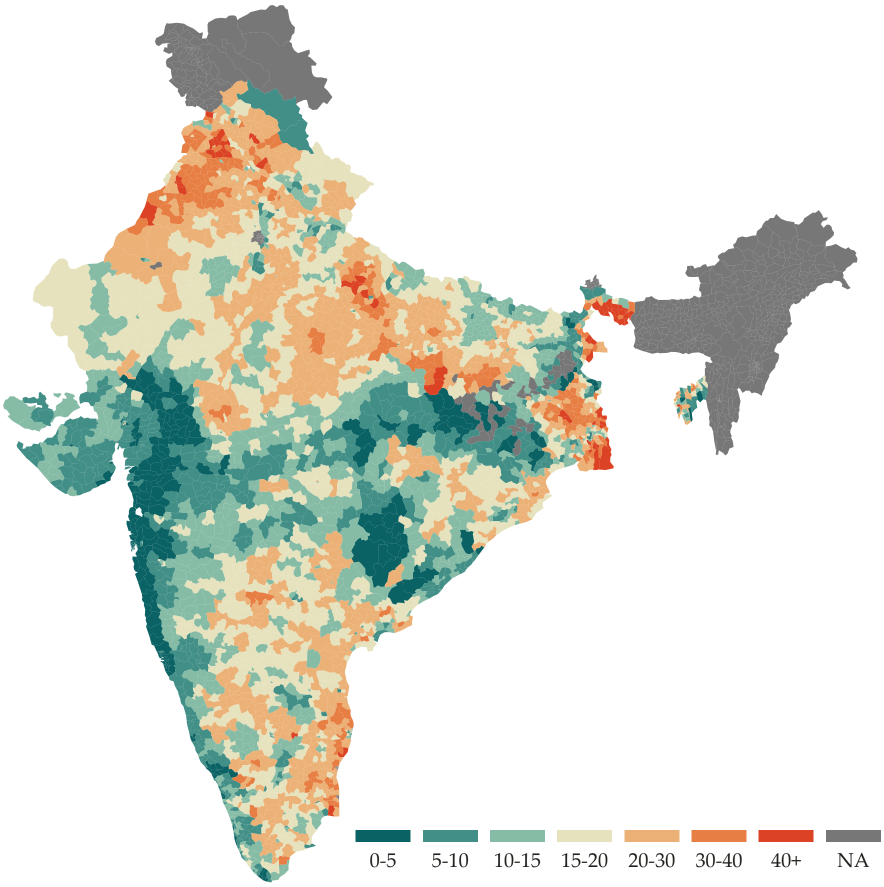
[22] Datasets of particular interest are the India Sub-National Problem Set (Marshall et al. 2005), the Varshney-Wilkonson Dataset on Hindu-Muslim Riots in India (Varshney and Wilkinson 2006), and Thiemo Fetzer's data on Naxalite conflict (Fetzer 2020).

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 3 presents a map showing the distribution of conflict events and fatalities. In the baseline specifications, I include all conflict data that is coded to the level corresponding to a town.[23]

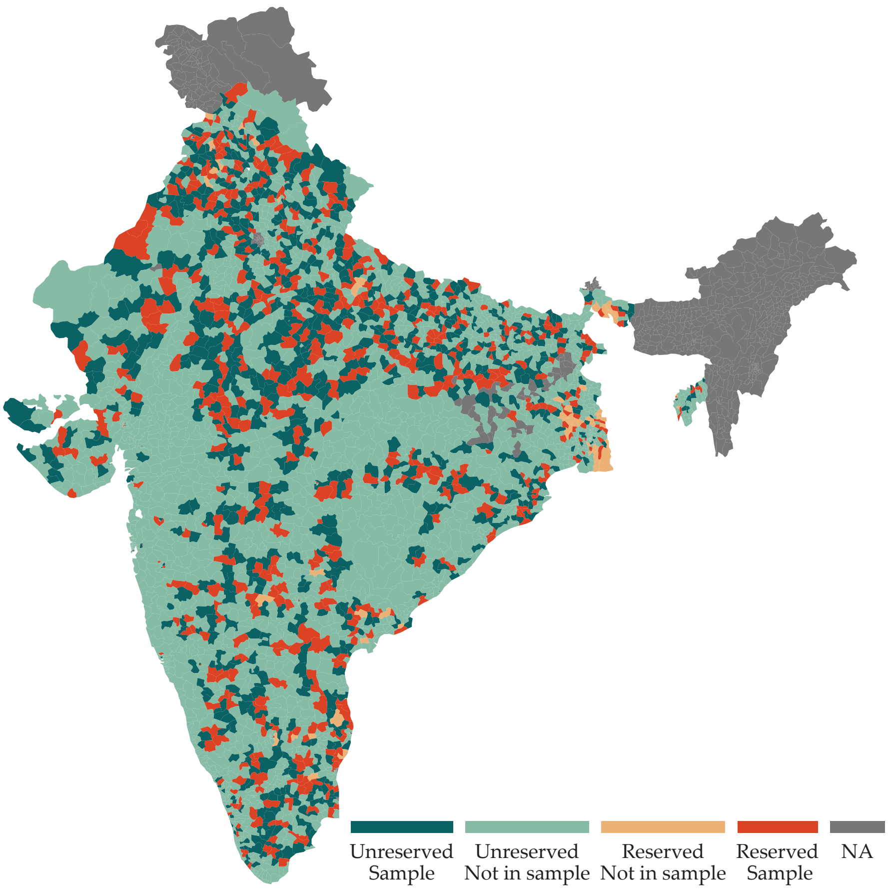
**Covariates:** I include several variables from the 2001 Census of India, obtained via the SHRUG-Dataset, in the analysis (Asher and Novosad 2019). While this is the most extensive available data at the constituency assembly level, one shortcoming is that not all assembly constituencies are included, 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.[24] Table 2a shows summary statistics for these variables by reservation status.

[23] I exclude some events that correspond to pure state actions, such as strategic developments. In section A2.1.1, I show that the main result also hold when restricting conflict to episodes that are explicitly related to castes.

[24] 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 $\delta$ from the model.

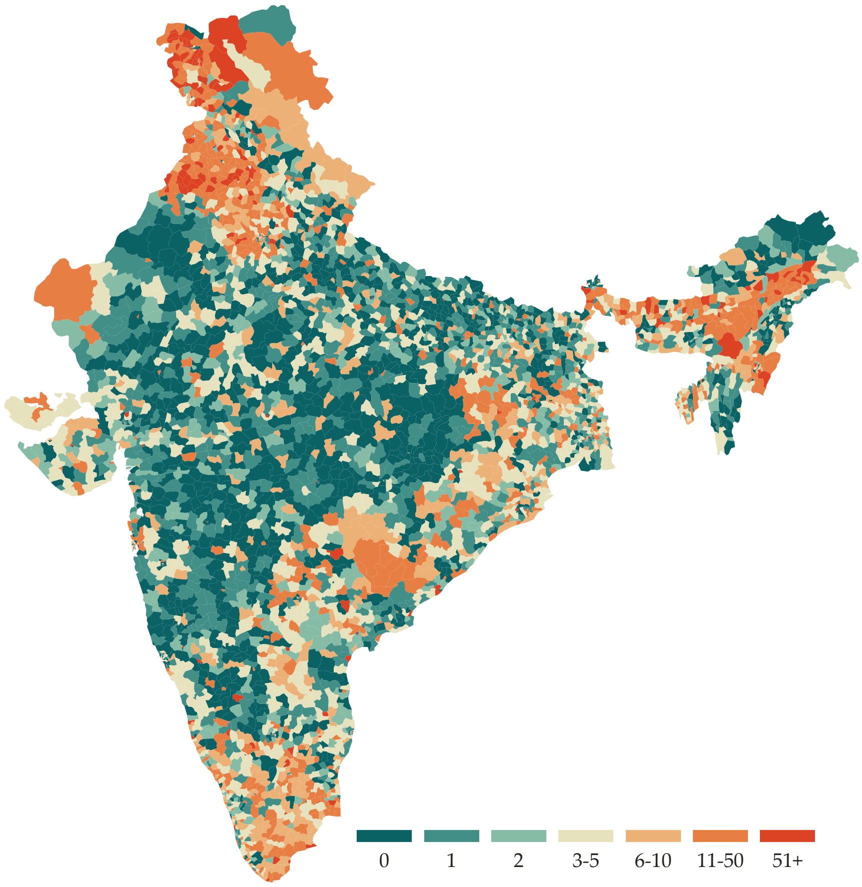



**(a)** SC population in 2001 in %, by assembly constituency

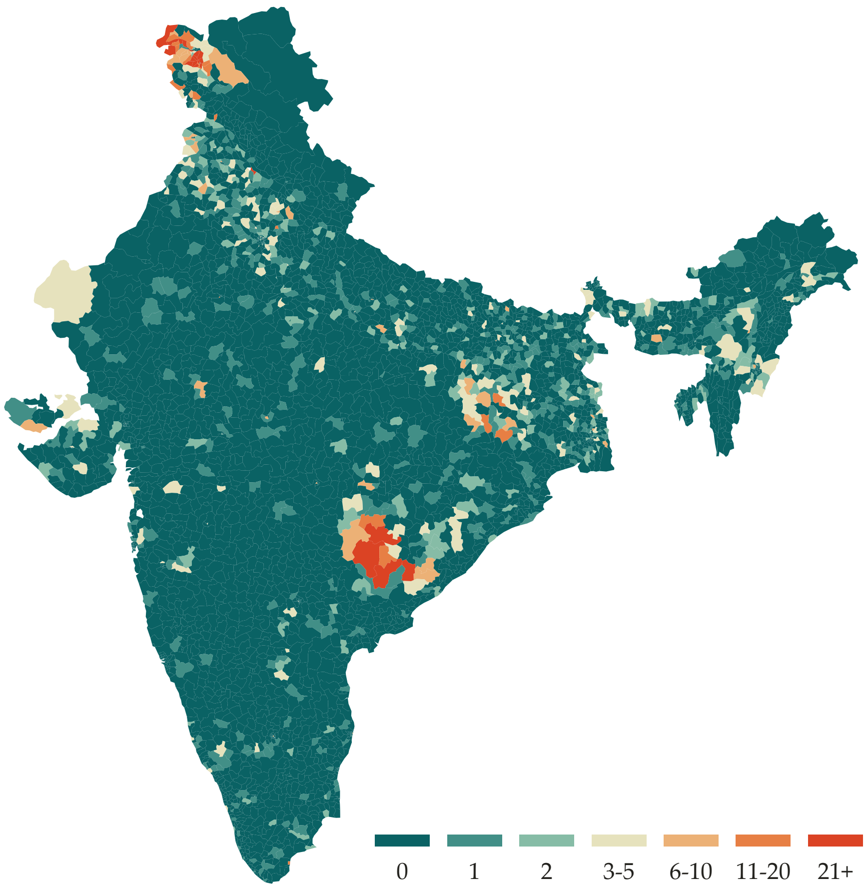



**(b)** Reservation status of assembly constituencies after 2008 delimitation

**Figure 2:** Map: Sample



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



**(b)** Number of fatalities from conflict, 2016-2020, by assembly constituency

**Figure 3:** Map: Conflict events in India

**Table 2:** Balance tables for assembly constituencies and villages in the sample

**(a)** Constituency assemblies

| Variable | (1) Runner-up | (2) Reserved | (3) Difference |
|---|---|---|---|
| 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 | | | 0.954 |
| p-value | | | 0.464 |
| Observations | 794 | 521 | 1,315 |

**(b)** IHDS villages

| Variable | (1) Unreserved | (2) Reserved | (3) Difference |
|---|---|---|---|
| Percent SC population | 23.131 | 29.293 | 6.162*** |
| | (19.292) | (19.809) | (0.001) |
| Percent Muslim population | 9.964 | 5.902 | -4.062** |
| | (22.237) | (14.895) | (0.040) |
| Percent ST population | 4.492 | 2.614 | -1.877* |
| | (12.778) | (8.187) | (0.097) |
| Mean of log income in sample | 11.115 | 11.045 | -0.070 |
| | (0.543) | (0.531) | (0.176) |
| Number of middle schools | 1.347 | 1.748 | 0.401** |
| | (1.839) | (2.023) | (0.026) |
| Number of primary schools | 2.223 | 2.544 | 0.322 |
| | (2.476) | (2.599) | (0.178) |
| Mean years of education in sample | 7.548 | 7.383 | -0.165 |
| | (2.538) | (2.343) | (0.485) |
| Accessibility by road | 1.879 | 1.864 | -0.015 |
| | (0.340) | (0.399) | (0.652) |
| Wald test statistic | | | 1.153 |
| p-value | | | 0.328 |
| Observations | 451 | 147 | 598 |

**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). For the Wald test statistic on the last line, a regression of reservation was run on all variables in the table (and in addition on state dummies for the village sample). I report the Wald statistic and associated p-value of 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%

## 4.2 Villages

For the village level, I rely on data from the India Human Development Survey (IHDS – Desai et al. 2010, 2015). The IHDS is a nationally representative household survey covering more than 40,000 households in 1,500 villages in India. I use data from the first (2005-06) and the second (2011-12) round of the survey.

**Reservations and sample for analysis:** In the second round of the IHDS survey, the reservation status as well as the actual caste for the *pradhan* of the village's GP was recorded. I build on an abundance of studies that make use of the random rotation of seats at the GP level as a natural experiment (Chattopadhyay and Duflo 2004; Besley et al. 2004; Beaman et al. 2009; Ban and Rao 2008). The random rotation allows to compare the outcomes in villages that had a reservation for SC *pradhans* to outcomes in villages that had no such reservation.

While this strategy seems close to a natural experiment, several threats to causal identification remain. The rotation system does not work like a lottery but has several rules that can lead to similar villages gaining reservation status in the same years.[25] Firstly, in most states, the rotation is carried on the level of the subdistrict. The proportion of GPs that is reserved is determined at the level of these subdistricts, so that GPs in different subdistricts have different probabilities of being reserved. As the IHDS data does not give precise enough geographic information, I am not able to take this fully into account. However, I include state-level dummies as well as the proportion of SC population in all specifications, which should absorb some of the variation in the propensity to be reserved.

Secondly, the standard rule in most states is to rank GPs within each subdistrict by SC population share, and rotate along blocks of GPs. This means that GPs similar SC population shares and other, potentially unobserved, factors amy be clustered within the same electoral cycle. I try to mitigate this concern by including all villages in the data, so that observations at different stages of the rotation cycle are included. As the IHDS is a national sample of villages, it is also unlikely that several villages belong to the same subdistrict. Table 2b shows that despite this, the balance is not perfect, as the mean of some covariates for reserved and unreserved villages are significantly different. Yet, the difference becomes insignficant once I control for the SC population share. As a final mitigation stragegy, I also include differences-in-differences estimates using the fact that none of the GPs that were reserved in the 2011 electoral cycle could have been reserved in 2005.

[25] There is a more recent literature that makes use of these rules. For example, Dunning and Nilekani (2013), Chauchard (2014), Parthasarathy (2017), and Sharan and Kumar (2019b, 2019b) estimate the effects of reservation using variants of the regression discontinuity design. As the identity of the villages in the survey is concealed, this approach is infeasible with the present data.

**Conflict Data:** I use two variables on conflict that are collected at the household level. The first variable proxies conflict in general and is the answer to question whether people in the respondent's village generally get along, or if there is conflict. The second variable proxies inter-caste conflict and is the answer to the question how much conflict there is among communities/*jatis* in the village. Both variables are trichotomous. I recode them so that higher values mean more conflict.

**Covariates:** I try to include a similar set of covariates as in the constituency level analysis. At the individual/household level, I include an indicator whether an individual was from a Scheduled Caste, a different backward caste (ST or OBC), or a forward caste. In addition, I include the log of the total household income and the years of education of the respondent. On the village level, I include the proportion of the population that belongs to the SC, the ST, and that is Muslim. I also include the number of primary and middle schools and an indicator for connectivity that codes whether a village is connected by a graded or ungraded road, or whether it has no access to a road at all. Table 2b shows means and standard deviations as well as p-values from t-tests for mean equality. While the difference in the population variables is a mechanical effect,[26] reserved villages also have, on average, 0.4 more middle schools than unreserved villages (significant at the 5% level). Despite this, the p-value for a Wald test of joint significance of all covariates, controlling for the SC population share, is not significant.

# 5 Results

## 5.1 Constituency-level evidence

To estimate the effect of reservations on conflict at the constituency level, I first estimate log-linear cross-sectional regressions of the form

$$\log\left(\text{Conflict}_i + 1\right) = \alpha + \beta_1 \text{Reserved}_i + \beta_2 \text{SC}_i + \beta_3 \text{Reserved}_i \times \text{SC}_i + \mathbf{x}_\mathbf{i}'\gamma + \epsilon_i \quad (17)$$

Where "Reserved" is an indicator whether a constituency was reserved, "SC" gives the proportion of the population that belongs to the Scheduled Castes, and **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. In the models with interaction terms, $\beta_1 \times 100$ gives the approximte effect of reservations, given that the SC population share is at the sample mean (around 22%). 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.

[26] As villages with higher SC population shares automatically have lower population shares of other communities, and are more likely to be reserved, there will be a correlation by construction.

Columns (1) to (4) of Table 3 show the results for these 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. For events, the interaction term is positive, but small and insignificant. Reservations are associated with around 3% fewer fatalities from conflict, but the coefficient is not significiant. However, the coefficient on the interaction term is negative and significant at the 10% level: For each standard deviation increase in the SC share of the population, reservations are associated with around 5% fewer conflicts. The overall model fit is moderate for events ($R^2 \approx 0.15$) and poor for fatalities ($R^2 \approx 0.05$). The inclusion of the interaction term does not substantially improve the model fit.

Not all covariates described above are included in the main specification. However, in appendix A2.1, I show that the results remain very stable when changing the combination of covariates included. Overall, the coefficients on the other covariates are of the expected sign. A larger SC population is associated with more conflict in all specifications, in line with the model when majority politicians are elected. A larger overall population is associated with slightly less conflict in most specifications. The population-normalized number of primary schools is associated with much lower conflict throughout all specifications. For connectivity by road, the sign is ambiguous.

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 estimate Poisson and negative binomial regression models as an alternative (Cameron and Trivedi 2013). In the Poisson model, the outcome $y_i$ is assumed to be Poisson distributed with density

$$f\left(y_i|\mathbf{x}_i\right) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, \quad y_i = 0, 1, 2, \ldots \tag{18}$$

where

$$\mathrm{E}\left[y_i|\mathbf{x}_i\right] = \mu_i = \exp\left(\mathbf{x}_i'\boldsymbol{\beta}\right) \tag{19}$$

As the log of the expected number of counts of the variable $y_i$ is linear in $\mathbf{x}_i'\boldsymbol{\beta}$, the interpretation of $\beta$ is that a one-unit change in the $x$-variable is associated with a change of $\beta$ in the expected number of (log) counts. In Poisson distributions, mean and variance are equal, an assumption that is not supported by the data.[27] Hence, in my preferred specification, I use a negative binomial regression that accounts for this overdispersion by estimating an additional parameter governing the relation between the mean and the variance. Accounting for this increases the standard errors in my regressions. In appendix A2.1, I show that the results are robust to using zero-inflated regression models accounting for this.

Columns (5) to (8) of Table 3 show the results for negative binomial regressions. Reser-

[27] 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.

vations are associated with around 20% fewer conflict events and fatalities ($\exp(-0.228) - 1 \approx -0.2$). However, while the coefficient on events is significant at the 5% level, the coefficient on fatalities is insignificant. The coefficient on the interaction term is large and positive for conflict events (significant at the 5% level), but negative for fatalities (not significant). The fact that the interaction term is weakly positive for conflict events, but negative for fatalities from conflict is puzzling from the perspective of the model. One potential explanation is that the mechanisms differ between low-intensity and high-intensity conflict, and that majority backlash might be particularly strong when the minority is large, making the appeasing effect of reservations smaller as the SC population becomes larger.

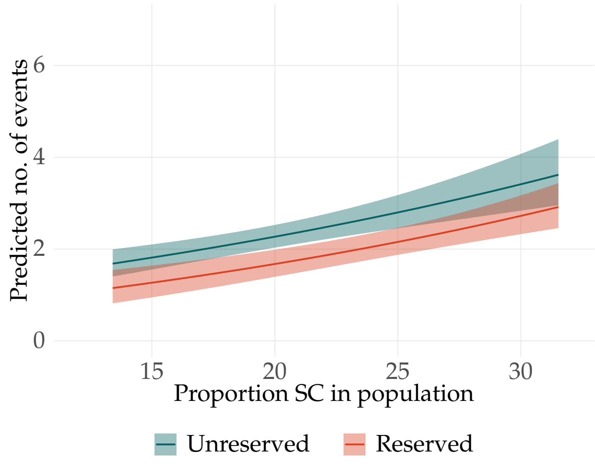
Figure 4 shows the predicted number of conflict events (left panels) and fatalities (right panels) by reservation status and SC population share, keeping all other control variables at their mean. The SC population share is varied between the 10th and the 90th percentile of the sample distribution (13 to 32 percent). Four observations are notable: First, as predicted, conflict increases in the SC population share for both reserved and unreserved constituencies. Second, conflict is lower in reserved compared to unreserved constituencies over nearl the whole range of the SC population share. Third, for conflict events, the difference in conflict levels decreases in the SC population share; this positive interaction term can not be explained by the model. Fourth, for conflict fatalities, the difference between reserved and unreserved constituencies increases in the SC population share, in line with the predictions of the model. However, confidence intervals are larger for fatalities, probably due to excess zeros in the fatalities data.

An important limitation to these results is the large spatial persistence of conflict. Conflict shows strong positive spatial correlation. One possibility to account for this would be to estimate spatial regression models. However, the definition of the sample of constituencies in the analysis prevents the full spatial structure of the data to be taken into account.

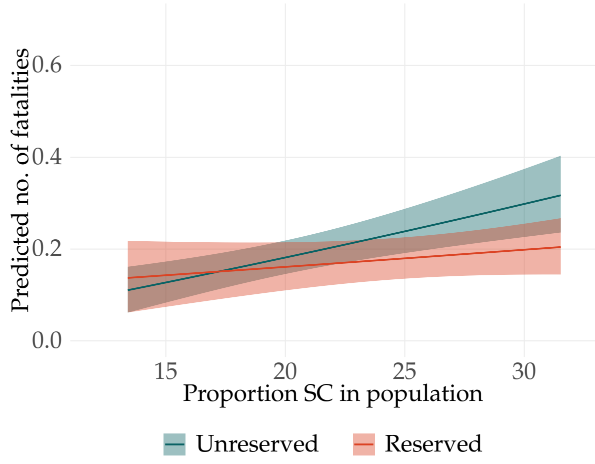
**Table 3:** Results: Constituency assemblies

| | OLS: log(Events+1) | | OLS: log(Fatalities+1) | | NB: Events | | NB: Fatalities | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Seat reserved for SC** | −0.193$^{***}$ | −0.194$^{***}$ | −0.033 | −0.030 | −0.228$^{**}$ | −0.256$^{***}$ | −0.272 | −0.236 |
| | (0.065) | (0.065) | (0.026) | (0.026) | (0.096) | (0.097) | (0.188) | (0.187) |
| Percent SC population | 0.229$^{***}$ | 0.218$^{***}$ | 0.046$^{***}$ | 0.068$^{***}$ | 0.267$^{***}$ | 0.158$^{**}$ | 0.213$^{**}$ | 0.289$^{**}$ |
| | (0.032) | (0.044) | (0.013) | (0.018) | (0.047) | (0.065) | (0.088) | (0.121) |
| **Reserved $\times$ SC pop** | | 0.022 | | −0.045$^{*}$ | | 0.224$^{**}$ | | −0.182 |
| | | (0.063) | | (0.026) | | (0.093) | | (0.176) |
| Population in 1000 | −0.003$^{***}$ | −0.003$^{***}$ | −0.0002 | −0.0002 | −0.006$^{***}$ | −0.007$^{***}$ | −0.001 | −0.001 |
| | (0.0004) | (0.0004) | (0.0002) | (0.0002) | (0.001) | (0.001) | (0.001) | (0.001) |
| Primary Schools per 1000 | −0.562$^{***}$ | −0.562$^{***}$ | −0.219$^{***}$ | −0.220$^{***}$ | −1.085$^{***}$ | −1.079$^{***}$ | −2.001$^{***}$ | −1.983$^{***}$ |
| | (0.094) | (0.094) | (0.039) | (0.038) | (0.143) | (0.143) | (0.337) | (0.335) |
| Percent paved roads | 0.006$^{***}$ | 0.006$^{***}$ | −0.003$^{***}$ | −0.003$^{***}$ | 0.005$^{**}$ | 0.005$^{**}$ | −0.018$^{***}$ | −0.019$^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.004) | (0.004) |
| Constant | 2.218$^{***}$ | 2.212$^{***}$ | 0.594$^{***}$ | 0.605$^{***}$ | 3.876$^{***}$ | 3.845$^{***}$ | 2.124$^{***}$ | 2.127$^{***}$ |
| | (0.241) | (0.242) | (0.099) | (0.099) | (0.364) | (0.364) | (0.687) | (0.685) |
| Observations | 993 | 993 | 993 | 993 | 993 | 993 | 993 | 993 |
| $R^2$ | 0.145 | 0.145 | 0.050 | 0.053 | | | | |
| Adjusted $R^2$ | 0.141 | 0.140 | 0.046 | 0.048 | | | | |
| Log Likelihood | | | | | −2,496.311 | −2,493.210 | −655.962 | −655.392 |
| Akaike Inf. Crit. | | | | | 5,004.621 | 5,000.421 | 1,323.924 | 1,324.784 |

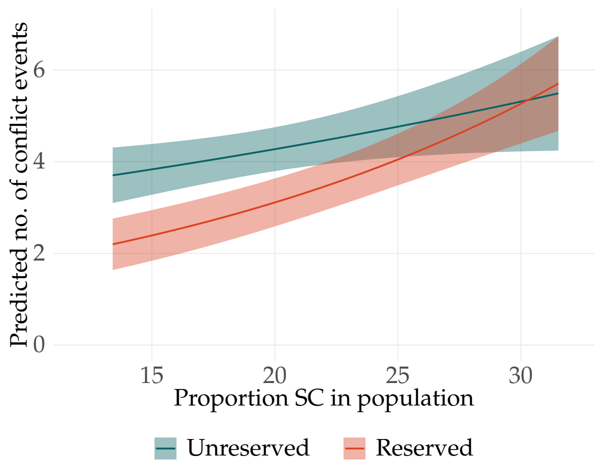
**Note:** Results from regressions of conflict events/fatalities for constituency assemblies in the sample as described in the main text.
OLS is for ordinary least squares, NB for negative binomial regression models.
Signficance levels: $^{*}$10%,$^{**}$ 5%,$^{***}$ 1%.



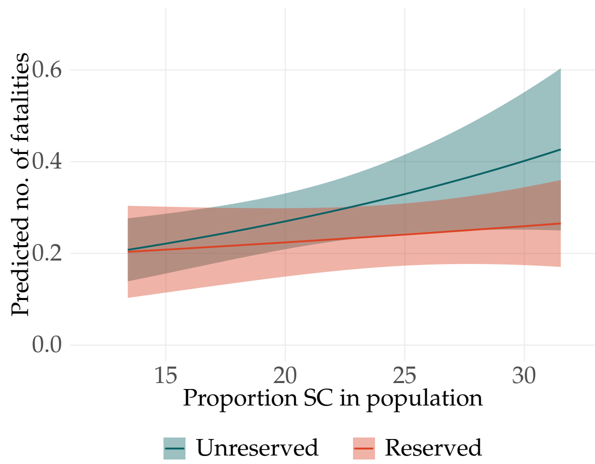

**(a)** Log-linear regression (log(events + 1))



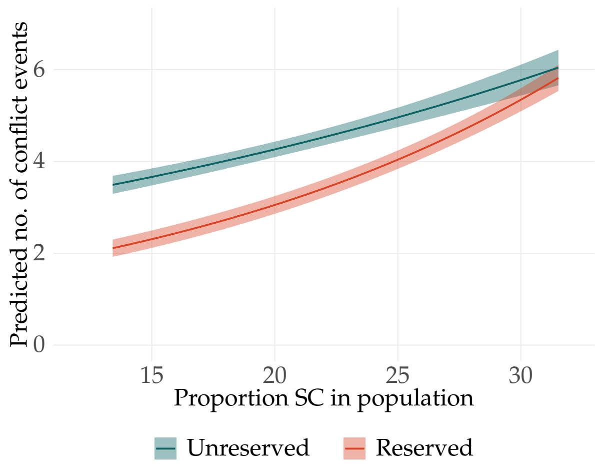

**(b)** Log-linear regression (log(fatalities + 1))



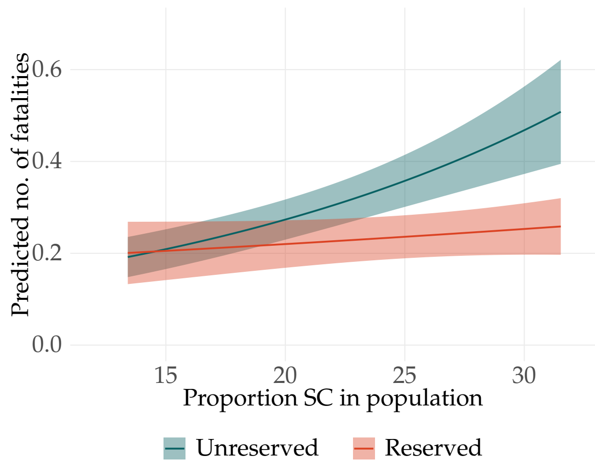

**(c)** Negative binomial regression for events




**(d)** Negative binomial regression for fatalities




**(e)** Poisson regression for events




**(f)** Poisson regression for fatalities

**Figure 4:** Predicted conflict by reservation status and SC population share

**Note:** Regressions include main and interaction terms for reservation status and SC population share, and the standard control variables. The top panel gives predicted values for the number of conflict events using a Poisson regression model. In the middle panel, the results for a negative binomial regression model are presented. The bottom panel gives the exponential of the predicted number of log(variable+1). The range of the SC population share corresponds to the 10th and 90th percentile of the sample distribution.

## 5.2 Village-level evidence

### 5.2.1 Cross-sectional evidence

For the village-level, I treat the trichotomous variable to be continuous and estimate linear regressions of the form

$$\text{Conflict}_i = \alpha + \beta_1 \text{Reserved}_i + \beta_2 \text{SC}_i + \beta_3 \text{Reserved}_i \times \text{SC}_i + \mathbf{x}_\mathbf{i}' \gamma + \epsilon_i \tag{20}$$

Table 4 shows the results of these regressions, with some output for the covariates omitted. I report standard errors clustered on the village level.[28] In line with the model, the effect of reservations is less appeasing in this setting of rotating reservations. The coefficient on reservation of the *pradhan* seat is positive in all specifications without interaction term. For conflict in general, the coefficient is relatively small: *Ceteris paribus*, reservation is associated with an increase in conflict by 0.02 in the three step scale, which corresponds to around 3% of the standard deviation of the conflict measure. For conflict between *jatis*, the coefficient is larger, and reservation is associated with an increase in conflict of around one sixth of a standard deviation. However, the coefficients are insignificant.

The interaction term is positive and signficant at the 5% level for conflict in general. For conflict between *jatis*, the coefficient on the interaction term is slightly smaller, with a slightly larger standard error, and therefore insignificant. Interpreting the results from column (4) of Table 4, reservation is associated with lower conflict in villages without any SCs. However, as the proportion of SCs rises to 25%, the impact of reservations on conflict becomes zero, and positive thereafter. This contradicts the result of the model that the effect of reservations should be more appeasing for higher minority population shares. One possible interpretation for this is that reserved *pradhans* in villages with larger SC populations are able to implement more extreme policies, an effect that is not considered in the model. However, as the coefficients on the covariates show, neither members of other backward castes nor of forward castes report significantly different conflict than the reference category, SC members.

[28] In initial regressions, reported in appendix A2.2, I used robust standard errors, and the coefficient was significant at the 5% level. However, simply using robust standard errors ignores the correlation of reservation and, potentially, other variables within villages. In the main specification, I therefore report standard errors clustered at the village level in order to account for the village-wide "assignment" to reservation, as recommended by Abadie et al. (2017).

**Table 4:** Reduced form regressions: Villages

| | Conflict in general | | | | Conflict between *jatis* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Pradhan seat reserved** | 0.017 | -0.134 | 0.020 | -0.133 | 0.088 | -0.040 | 0.096 | -0.033 |
| | (0.063) | (0.101) | (0.063) | (0.100) | (0.069) | (0.112) | (0.070) | (0.114) |
| Proportion SC population | 0.048 | -0.122 | 0.076 | -0.099 | -0.021 | -0.165 | -0.019 | -0.166 |
| | (0.147) | (0.157) | (0.148) | (0.158) | (0.145) | (0.143) | (0.147) | (0.146) |
| **Reserved $\times$ SC pop** | | 0.518** | | 0.524** | | 0.441 | | 0.442 |
| | | (0.249) | | (0.251) | | (0.269) | | (0.275) |
| Respondent from backward caste | | | 0.029 | 0.031 | | | -0.040 | -0.039 |
| | | | (0.034) | (0.034) | | | (0.039) | (0.039) |
| Respondent from forward caste | | | 0.015 | 0.009 | | | -0.009 | -0.014 |
| | | | (0.036) | (0.036) | | | (0.038) | (0.039) |
| Log(Total income) | | | -0.011 | -0.013 | | | -0.014 | -0.016 |
| | | | (0.012) | (0.012) | | | (0.011) | (0.011) |
| N | 11,566 | 11,566 | 11,375 | 11,375 | 11,560 | 11,560 | 11,369 | 11,369 |
| Number of villages | 583 | 583 | 583 | 583 | 583 | 583 | 583 | 583 |
| $R^2$ | 0.12 | 0.12 | 0.12 | 0.13 | 0.11 | 0.11 | 0.11 | 0.11 |
| Mean of DV | 0.52 | 0.52 | 0.52 | 0.52 | 0.52 | 0.52 | 0.52 | 0.52 |
| Village level controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual level controls | | | ✓ | ✓ | | | ✓ | ✓ |
| State dummies | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

**Note:** Standard errors clustered by village in parentheses. Village level controls: Muslim share of population, Scheduled Tribe share of population, number of primary and middle schools, connectivity by road. Individual level controls: Caste classification, log(Income), years of education. Significance levels: *10%, **5%, ***1%

### 5.2.2 Differences-in-differences estimates

To mitigate concerns about similarity of reserved villages within one electoral cycle, I merge the data from the second IHDS wave to data from the first wave. Using this panel data set, I am able to estimate differences-in-differences (DiD) regressions of the form:

$$\text{Conflict}_{it} = \alpha_i + \delta_t + \beta\text{Reserved}_{it} + \gamma\text{Income}_{it} + \epsilon_{it} \tag{21}$$

Because of differences in the questionnaire between survey waves and the stability of village-level data over time, I do not use village-level controls and include only total household income as control variable. One major challenge in the estimation of the parameter of interest, $\beta$, is that the village-level reservation status was only elicited during the second wave of the IHDS. I use the fact that villages that were reserved in 2011 could not have been reserved in 2005. Similarly, out of the villages unreserved in 2011, a proportion $\theta$ has been reserved in 2005. Using this observation, I can give a range on the DiD-estimate, assuming either $\theta = 0$ or $\theta = 1$. In Appendix A3, I use Monte-Carlo simulations to show that this is a valid approach, assuming that the treatment is randomized in the first period. In fact, if the proportion of treated villages in the first period is known, a weighted combination between the two cases can give an unbiased estimate of the true treatment effect. Interestingly, coefficient and standard error are scaled by the same number, so that the t-statistic does not depend on the exact proportion of reserved villages in the first period.

Table 5 presents the DiD-estimates. As in the results above, standard errors are clustered by village, and appendix A2.2 reports heteroskedasticity-robust standard errors. Reservations do not seem to be related to general conflict, as the coefficient is close to zero. Between 2005 and 2011, the reported overall conflict level has decreased by around one third of a standard deviation. For conflict between *jatis*, reservation is associated with slightly more conflict, ranging between 5% and 10% of a standard deviation. While this coefficient is significant with robust standard errors, it turns insignificant when using standard errors clustered at the village level. Unlike for general conflict, reported conflict between *jatis* has increased over time. Throughout all specifications, higher income is associated with slightly less reported conflict; however, the coefficient is insignificant. The relatively low within-$R^2$ indicates that the differences-in-differences model is unable to explain the variation in conflict well.

**Table 5:** DiD Estimates: Villages

| | Conflict in general $\theta = 0$ | $\theta = 1$ | Conflict between *jatis* $\theta = 0$ | $\theta = 1$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Pradhan seat reserved** | -0.006 | -0.003 | 0.061 | 0.031 |
| | (0.093) | (0.046) | (0.068) | (0.034) |
| Log(Total income) | -0.019 | -0.019 | -0.007 | -0.007 |
| | (0.020) | (0.020) | (0.013) | (0.013) |
| Time trend | -0.201*** | -0.204*** | 0.088** | 0.118*** |
| | (0.050) | (0.046) | (0.039) | (0.034) |
| Constant | 0.923*** | 0.925*** | 0.482*** | 0.460*** |
| | (0.221) | (0.228) | (0.139) | (0.136) |
| N | 22,482 | 22,482 | 22,476 | 22,476 |
| Number of villages | 581 | 581 | 581 | 581 |
| $R^2$ (within) | 0.04 | 0.04 | 0.02 | 0.02 |
| Mean of DV | 0.62 | 0.62 | 0.46 | 0.46 |

**Note:** Standard errors clustered by village in parentheses.
Significance levels: *10%, **5%, ***1%.

# 6 Conclusion

This paper adds to the recent literature that explains heterogenous and unintended consequences of political reservation by extending the analysis to subnational conflict. I showed that reserved constituencies have experienced fewer conflict events over the last four years, while the effect of reservations on conflict at the village level is more opaque. An interpretation in line with the theoretical model is that reelection incentives may be moderating the link between reservations and conflict.

Empirically, this paper is limited by the inherent difficulty to estimate the effect of the presence of the reservation system as a whole due to spillover effects. In the context of villages, the rotation cycle may also change the incentives of majority incumbents, a concern for which Parthasarathy (2017) presents some empirical evidence. If this is true, the Stable Unit Treatment Value Assumption (SUTVA) is violated, as incumbent politicians in the control group may react to future reservations. As a consequence, the estimated effect only capture the relative difference between reserved and unreserved villages.

For constituencies, my results are limited by the fact that the estimates are only valid for constituencies around the cutoff. While this study is optimistic about this sample, extrapolating the results in order to infer policy recommendations for more reservations is unwarranted. Moreover, the present analysis ignores potential interactions between different political levels. For example, having SC politicians from the local to the national level may have different impacts than a single *pradhan* in an otherwise high-caste dominated environment. Sharan and Kumar (2019a) present some evidence and potential policy solutions for this channel.

As an extension of this analysis, it would be interesting to use variation in the total number of seats reserved by district. This higher level of aggregation would take into account spillover effects, but also give the opportunity to use the rich district-level conflict data available for India. Another 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.

# References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey Wooldridge. 2017. *When Should You Adjust Standard Errors for Clustering?* Working Paper, Working Paper Series 24003. National Bureau of Economic Research.

Acemoglu, Daron, and James A Robinson. 2019. *The narrow corridor: States, societies, and the fate of liberty*. Penguin Press.

Alesina, Alberto, Reza Baqir, and William Easterly. 1999. "Public Goods and Ethnic Divisions". *The Quarterly Journal of Economics* 114 (4): 1243–1284.

Anderson, Siwan, Patrick Francois, and Ashok Kotwal. 2015. "Clientelism in Indian Villages". *American Economic Review* 105 (6): 1780–1816.

Asher, Sam, and Paul Novosad. 2019. "The Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG)". Downloaded on May 28th, 2020.

Ban, Radu, and Vijayendra Rao. 2008. "Tokenism or Agency? The Impact of Women's Reservations on Village Democracies in South India". *Economic Development and Cultural Change* 56 (3): 501–530.

Bardhan, Pranab, and Dilip Mookherjee. 2010. "Determinants of Redistributive Politics: An Empirical Analysis of Land Reforms in West Bengal, India". *American Economic Review* 100 (4): 1572–1600.

Beaman, Lori, Raghabendra Chattopadhyay, Esther Duflo, Rohini Pande, and Petia Topalova. 2009. "Powerful Women: Does Exposure Reduce Bias?" *The Quarterly Journal of Economics* 124 (4): 1497–1540.

Bertrand, Marianne, Rema Hanna, and Sendhil Mullainathan. 2010. "Affirmative action in education: Evidence from engineering college admissions in India". *Journal of Public Economics* 94 (1): 16–29.

Besley, Timothy, and Anne Case. 1995. "Does Electoral Accountability Affect Economic Policy Choices? Evidence from Gubernatorial Term Limits". *The Quarterly Journal of Economics* 110, no. 3 (): 769–798.

Besley, Timothy, and Stephen Coate. 1997. "An Economic Model of Representative Democracy". *The Quarterly Journal of Economics* 112 (1): 85–114.

Besley, Timothy, Rohini Pande, Lupin Rahman, and Vijayendra Rao. 2004. "The Politics of Public Good Provision: Evidence from Indian Local Governments". *Journal of the European Economic Association* 2 (2-3): 416–426.

Besley, Timothy, and Torsten Persson. 2011. "The Logic of Political Violence". *The Quarterly Journal of Economics* 126 (3): 1411–1445.

Bhavnani, Rikhil R. 2009. "Do Electoral Quotas Work after They Are Withdrawn? Evidence from a Natural Experiment in India". *American Political Science Review* 103 (01): 23–35.

– . 2017. "Do the Effects of Temporary Ethnic Group Quotas Persist? Evidence from India". *American Economic Journal: Applied Economics* 9 (3): 105–123.

Bhavnani, Rikhil R., and Alexander Lee. 2019. "Does Affirmative Action Worsen Bureaucratic Performance? Evidence from the Indian Administrative Service". *American Journal of Political Science*, no. Forthcoming.

Bohlken, Anjali Thomas, and Ernest John Sergenti. 2010. "Economic growth and ethnic violence: An empirical investigation of Hindu-Muslim riots in India". *Journal of Peace Research* 47 (5): 589–600.

Cameron, A. Colin, and Pravin K. Trivedi. 2013. *Regression analysis of count data*. 2nd ed. Cambridge University Press.

Chattopadhyay, Raghabendra, and Esther Duflo. 2004. "Women as Policy Makers: Evidence from a Randomized Policy Experiment in India". *Econometrica* 72 (5): 1409–1443.

Chauchard, Simon. 2014. "Can Descriptive Representation Change Beliefs about a Stigmatized Group? Evidence from Rural India". *American Political Science Review* 108 (2): 403–422.

Chin, Aimee, and Nishith Prakash. 2011. "The redistributive effects of political reservation for minorities: Evidence from India". *Journal of Development Economics* 96 (2): 265–277.

Collier, Paul, and Anke Hoeffler. 2004. "Greed and grievance in civil war". *Oxford Economic Papers* 56 (4): 563–595.

– . 1998. "On economic causes of civil war". *Oxford Economic Papers* 50 (4): 563–573.

Community Created Maps of India. 2020. *Assembly-Constituencies: Shapefiles*. Dataset. Downloaded on May 28th, 2020. Datameet.

Delimitation Commission of India. 2008. "Changing Face of Electoral India: Delimitation 2008". Retrieved on May 28th, 2020. `https://eci.gov.in/files/file/7164-changing-face-of-electoral-india-delimitation-2008-volume1/`.

Desai, Sonalde, Reeve Vanneman, and NCAER. 2010. *India Human Development Survey-I (IHDS-I), 2005*. Dataset. Downloaded on May 28th, 2020. Inter-university Consortium for Political and Social Research.

– . 2015. *India Human Development Survey-II (IHDS-II), 2011-12.* Dataset. Downloaded on May 28th, 2020. Inter-university Consortium for Political and Social Research.

Deshpande, Ashwini, and Thomas E. Weisskopf. 2014. "Does Affirmative Action Reduce Productivity? A Case Study of the Indian Railways". *World Development* 64:169–180.

Dube, Oeindrila, and Juan F. Vargas. 2013. "Commodity Price Shocks and Civil Conflict: Evidence from Colombia". *The Review of Economic Studies* 80 (4): 1384–1421.

Dunning, Thad, and Janhavi Nilekani. 2013. "Ethnic Quotas and Political Mobilization: Caste, Parties, and Distribution in Indian Village Councils". *American Political Science Review* 107 (1): 35–56.

Dutta, Puja, Rinku Murgai, Martin Ravallion, and Dominique van de Walle. 2014. *Right to Work? Assessing India's Employment Guarantee Scheme in Bihar*. Tech. rep. Equity and Development Series: World Bank.

Ferraz, Claudio, and Frederico Finan. 2011. "Electoral Accountability and Corruption: Evidence from the Audits of Local Governments". *American Economic Review* 101 (4): 1274–1311.

Fetzer, Thiemo. 2020. "Can Workfare Programs Moderate Conflict? Evidence from India". Jvz062 (Advance Article), *Journal of the European Economic Association*.

Girard, Victoire. 2016. *Mandated political representation and crimes against the low castes*. Working Paper. WIDER Working Paper 2016/74.

Holzer, Harry, and David Neumark. 2000. “Assessing Affirmative Action”. *Journal of Economic Literature* 38 (3): 483–568.

Hughes, Melanie M. 2011. “Intersectionality, Quotas, and Minority Women’s Political Representation Worldwide”. *American Political Science Review* 105 (3): 604–620.

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

Iyer, Lakshmi, and Maya Shivakumar. 2009. “Electoral redistricting in the world’s largest democracy: An evaluation”.

Jensenius, Francesca Refsum. 2015. “Development from Representation? A Study of Quotas for the Scheduled Castes in India”. *American Economic Journal: Applied Economics* 7 (3): 196–220.

Krook, Mona Lena, and Diana Z. O’Brien. 2010. “The Politics of Group Representation: Quotas for Women and Minorities Worldwide”. *Comparative Politics* 42 (3): 253–272.

Lindbeck, Assar, and Jörgen W. Weibull. 1987. “Balanced-budget redistribution as the outcome of political competition”. *Public Choice* 52 (3): 273–297.

Marshall, Monty G., Shonali Sardesi, and Donna Ramsey Marshall. 2005. *India Sub-National Problem Set, 1960-2004*. Dataset. Downloaded on May 28th, 2020. Political Instability Task Force.

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti. 2004. “Economic Shocks and Civil Conflict: An Instrumental Variables Approach”. *Journal of Political Economy* 112 (4): 725–753.

Mitra, Anirban, and Debraj Ray. 2014. “Implications of an Economic Theory of Conflict: Hindu-Muslim Violence in India”. *Journal of Political Economy* 122 (4): 719–765.

Munshi, Kaivan, and Mark Rosenzweig. 2018. “Ethnic Diversity and the Under-Supply of Local Public Goods”.

Narula, Smita. 1999. *Broken People: Caste Violence Against India’s "Intouchables"*. Tech. rep. Human Rights Watch Asia.

Natraj, Ashwini. 2011. “Some unintended consequences of political quotas”. Working Paoer.

NDTV India. 2016. “Haryana Jat Agitation Death Toll Rises To 30”. `https://www.ndtv.com/india-news/haryana-jat-agitation-death-toll-rises-to-30-1281690`.

O’Connell, Stephen D. 2020. “Can Quotas Increase the Supply of Candidates for Higher-Level Positions? Evidence from Local Government in India”. *The Review of Economics and Statistics* 102 (1): 65–78.

Osborne, Martin J., and Al Slivinski. 1996. “A Model of Political Competition with Citizen-Candidates”. *The Quarterly Journal of Economics* 111 (1): 65–96.

Pande, Rohini. 2003. “Can Mandated Political Representation Increase Policy Influence for Disadvantaged Minorities? Theory and Evidence from India”. *American Economic Review* 93 (4): 1132–1151.

Parthasarathy, Ramya. 2017. “Ethnic Quotas as Term-Limits: Caste and Distributive Politics in South India”. *Comparative Political Studies* 50 (13): 1735–1767.

Persson, Torsten, and Guido Tabellini. 2000. *Political Economics*. MIT Press.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen. 2010. "Introducing ACLED: An Armed Conflict Location and Event Dataset". *Journal of Peace Research* 47, no. 5 (): 651–660.

Rao, M Govinda, and Nirvikar Singh. 2003. "The political economy of center-state fiscal transfers in India". *World Bank Technical Paper*: 69–124.

Rößler, Martin, Jonathan Old, and Patrick Zwerschke. 2019. "(When) Do Democracies Repress Less?" Unpublished Manuscript.

Sharan, M.R., and Chinmaya Kumar. 2019a. *Something to Complain About: How Minority Representatives Overcome Ethnic Differences*. Job Market Paper. Harvard University.

– . 2019b. "The Distributional Consequences of Political Reservation". Unpublished Working Paper.

Siddique, Zahra. 2011. "Evidence on Caste Based Discrimination". Labour markets in developing countries, *Labour Economics* 18:S146–S159.

Times of India. 2016. "Why the jat community is up in arms". 20 February 2016. Retrieved on May 28th, 2020. `https://timesofindia.indiatimes.com/india/Why-the-jat-community-is-up-in-arms/articleshow/51064424.cms`.

Vanden Eynde, Oliver. 2018. "Targets of Violence: Evidence from India's Naxalite Conflict". *The Economic Journal* 128 (609): 887–916.

Varshney, Ashutosh. 2002. *Ethnic Conflict and Civic Life: Hindus and Muslims in India*. New Haven, CT: Yale University Press.

Varshney, Ashutosh, and Steven. Wilkinson. 2006. *Varshney-Wilkinson Dataset on Hindu-Muslim Violence in India, 1950-1995*. Dataset. Inter-university Consortium for Political and Social Research.

Wilkinson, Steven. 2004. *Votes and Violence: Electoral Competition and Ethnic Riots in India*. New York: Cambridge University Press.

# A1 Details and proofs for the model

## A1.1 Proof for Proposition 2

*Proof.* Reservation increases the quantity of the public good provided. We can hence determine the sign of the effect by using Equation 4.

$$\frac{\partial \frac{\partial n}{\partial x}}{\partial s} = (1 - y_A)(x - x_A) - (1 - y_A - \delta)(x - x_B) \tag{22}$$

$$= \delta(x - x_B) - (1 - y_A)(\Delta x) \tag{23}$$

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

$$\frac{\partial \frac{\partial n}{\partial x}}{\partial \delta} = -(1 - s)(x - x_B) \tag{24}$$

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. □

## A1.2 Proof for Proposition 4

*Proof.* If $\alpha \leq \beta$, (19) is trivially positive. Take the case where $\alpha = \beta$. Small increases in $s$ and $\delta$ increase $\alpha$ and decrease $\beta$ continuously, leading to a continuous decrease in the term in parentheses in (19). Since this is strictly above zero at $\alpha = \beta$, for at least some range where $\alpha > \beta$, the term remains positive. □

# A2 Robustness Checks

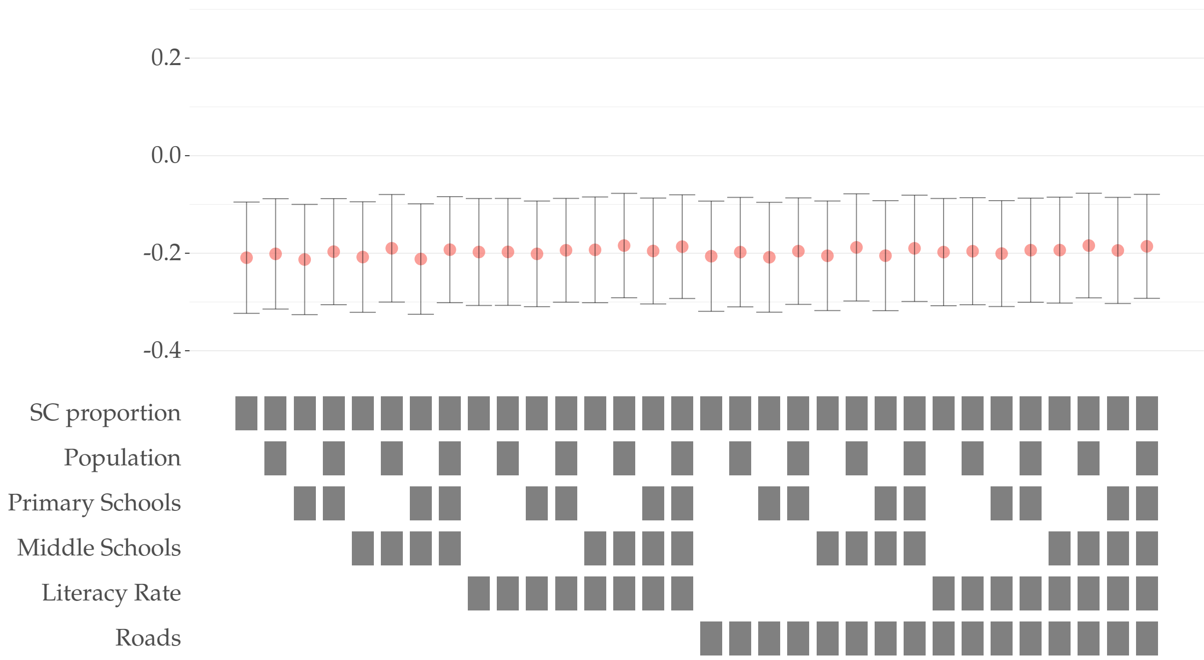
## A2.1 Constituencies

To show that the results of the log-linear OLS specification are robust to the inclusion of different combinations of covariates, Figure 5 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, so that all possible combinations are shown. The results remain very stable throughout the exercise.

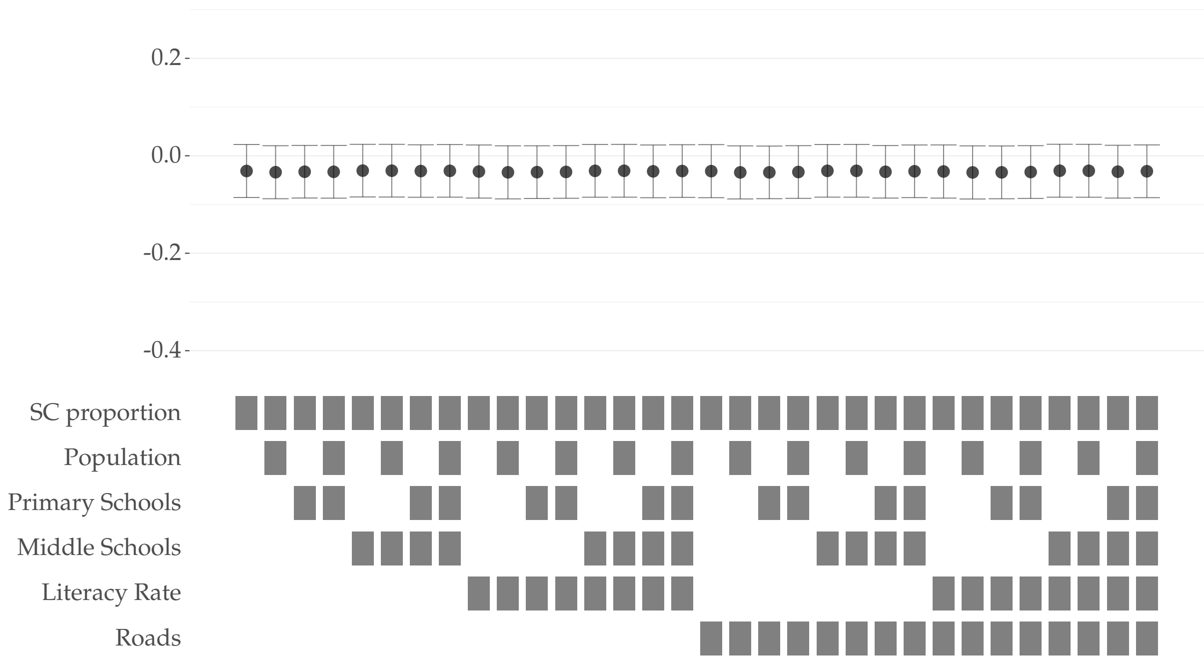
Table 6 presents the estimates from the Poisson models that are not included in the main text, as the data indicates overdisperion.

Figure 6 presents estimates from zero-inflated regression models. As the current version of the `pscl` package for the estimation of zero-inflated models in `R` does not support the calculation of standard errors for predictions, I bootstrap confidence intervals with 5,000 repetitions.

Zero-inflated models are considered appropriate in models with count data with excess zeros (Cameron and Trivedi 2013). The model is estimated in two parts: In the first part, a logistic regression is run to predict the probability to observe a non-zero outcome. In




**(a)** Robustness checks for events




**(b)** Robustness checks for fatalities

**Figure 5:** Robustness of coefficient on conflict in linear models

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

the second part, a standard count model data is estimated to predict the number of outcomes observed. The predicted value of the outcome variable is then:

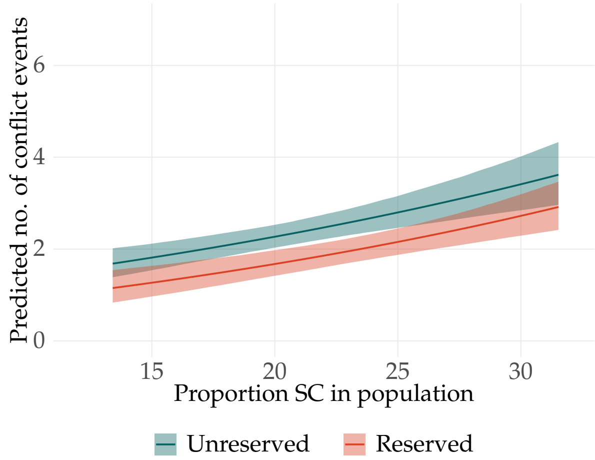
$$E[y_i|x_i] = (\pi_i|x_i) \cdot (\mu_i|x_i)$$

where $(\pi_i|x_i)$ is the predicted probability of observing a non-zero outcome, conditional on $x_i$, and $(\mu_i|x_i)$ is the predicted number of outcomes, conditional on $x_i$.

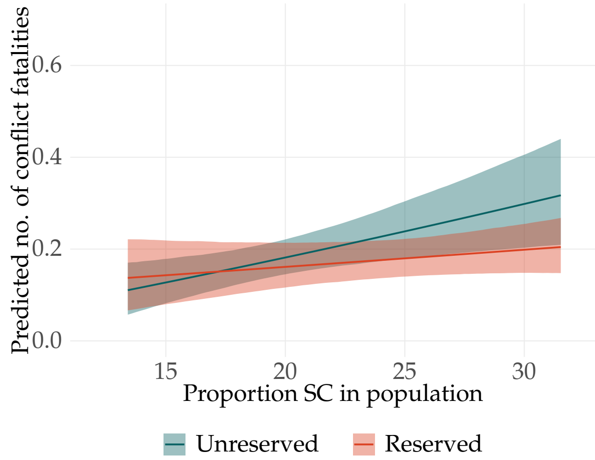
While the confidence intervals are slightly larger than those in the results with standard count data models, the overall interpretation does not change.

**Table 6:** Robustness Check: Poisson regressions for constituency assemblies

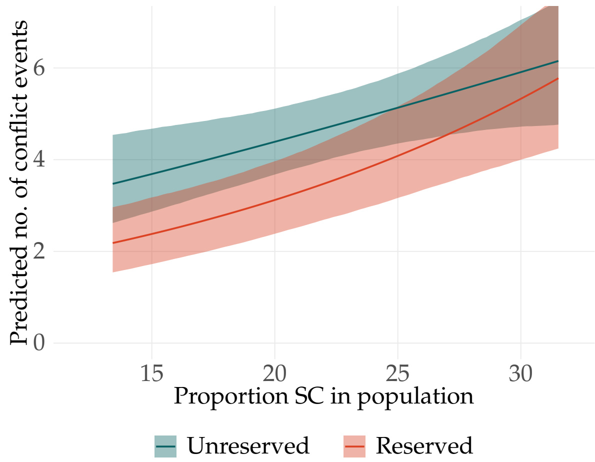
| | *Poisson* | | | |
|---|---|---|---|---|
| | Events | | Fatalities | |
| | (1) | (2) | (3) | (4) |
| **Seat reserved for SC** | −0.209*** | −0.283*** | −0.392*** | −0.296** |
| | (0.030) | (0.033) | (0.124) | (0.124) |
| Percent SC population | 0.311*** | 0.220*** | 0.267*** | 0.391*** |
| | (0.013) | (0.019) | (0.053) | (0.068) |
| **Reserved × SC pop** | | 0.187*** | | −0.290*** |
| | | (0.026) | | (0.107) |
| Population in 1000 | −0.006*** | −0.006*** | −0.001 | −0.001 |
| | (0.0002) | (0.0002) | (0.001) | (0.001) |
| Primary Schools per 1000 | −1.272*** | −1.259*** | −1.846*** | −1.867*** |
| | (0.051) | (0.051) | (0.222) | (0.223) |
| Percent paved roads | 0.005*** | 0.005*** | −0.017*** | −0.017*** |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| Constant | 3.794*** | 3.779*** | 1.721*** | 1.792*** |
| | (0.119) | (0.119) | (0.390) | (0.390) |
| Observations | 993 | 993 | 993 | 993 |
| Log Likelihood | −5,609.053 | −5,584.162 | −792.379 | −788.709 |
| Akaike Inf. Crit. | 11,230.100 | 11,182.330 | 1,596.758 | 1,591.417 |
| **Note:** | Results from Poisson regressions of conflict events and fatalities for constituency assemblies in the sample. Signficance levels: *10%,** 5%,*** 1%. | | | |



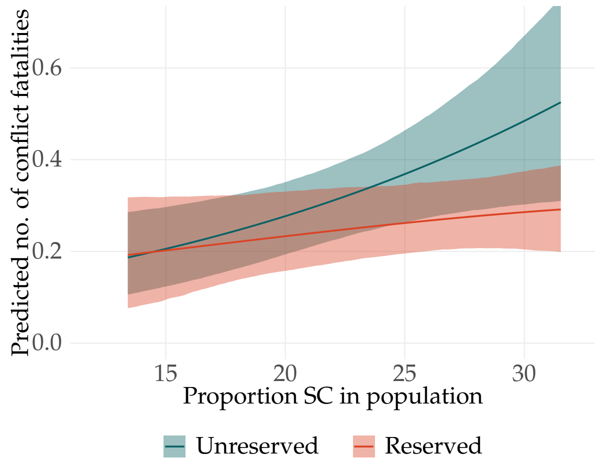

**(a)** Log-linear regression (log(events + 1))



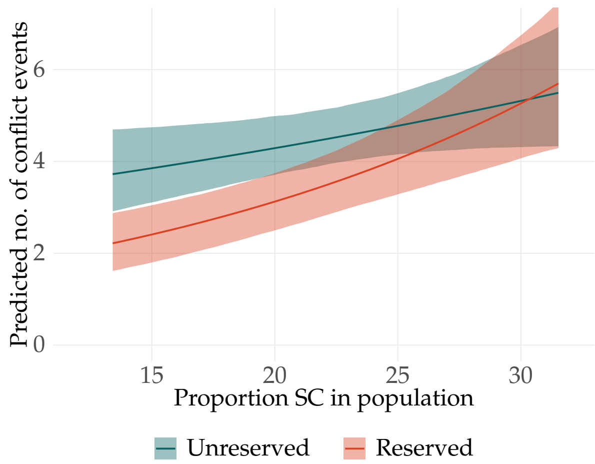

**(b)** Log-linear regression (log(fatalities + 1))



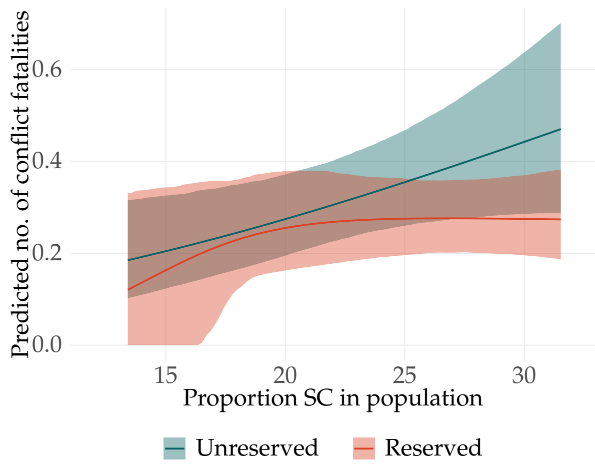

**(c)** Zero-inflated neg. binom. for events




**(d)** Zero-inflated neg. binom. for fatalities




**(e)** Zero-inflated poisson for events




**(f)** Zero-inflated poisson for fatalities

**Figure 6:** Robustness Check: Predicted conflict by reservation status and SC population share, Zero-inflated regression models

**Note:** Regressions include main and interaction terms for reservation status and SC population share, and the standard control variables. In all models, standard errors were bootstrapped. The top panel reproduces the log-linear regression from the main specification. The middle panel reports results for zero-inflated negative binomial, the bottom panel for zero-inflated poisson regression models. The range of the SC population share corresponds to the 10th and 90th percentile of the sample distribution.

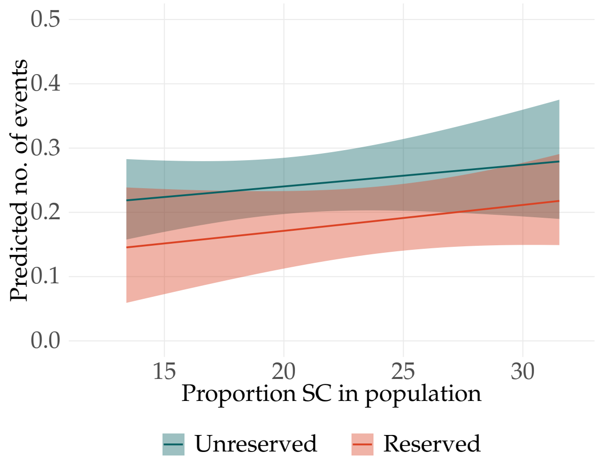
#### A2.1.1 Caste-related conflict only

Table 7 shows results from log-linear OLS, negative binomial, and Poisson regressions when using only the 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 in the main results, the coefficient on the interaction term is positive, but it is not significant here. As an important limitation, the analysis has much lower power than the main analysis because the number of events included is reduced significantly. Figure 7 shows the results graphically. As there are only 213 associated fatalities in the sample, I do not report results for them.

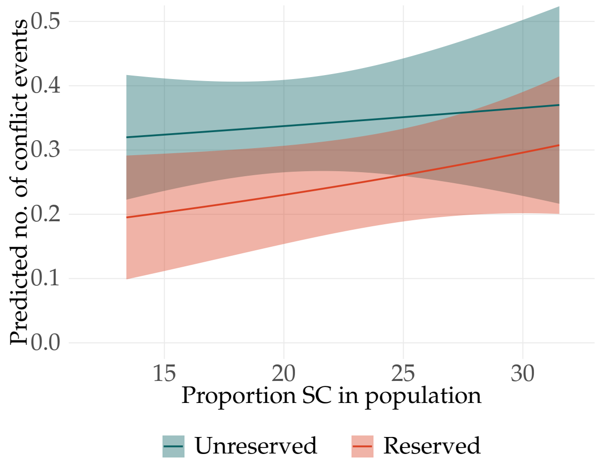
**Table 7:** Robustness Check: Constituency assemblies, caste-related conflict only

| | OLS: log(Events+1) | | NB: Events | | Poisson: Events | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Seat reserved for SC** | $-0.056^{*}$ | $-0.056^{*}$ | $-0.331^{*}$ | $-0.348^{*}$ | $-0.450^{***}$ | $-0.489^{***}$ |
| | (0.030) | (0.030) | (0.182) | (0.185) | (0.109) | (0.116) |
| Percent SC population | 0.022 | 0.019 | 0.118 | 0.059 | $0.189^{***}$ | $0.138^{**}$ |
| | (0.015) | (0.021) | (0.086) | (0.117) | (0.048) | (0.062) |
| **Reserved × SC pop** | | 0.005 | | 0.124 | | 0.128 |
| | | (0.030) | | (0.173) | | (0.097) |
| Population in 1000 | $-0.001^{***}$ | $-0.001^{***}$ | $-0.007^{***}$ | $-0.007^{***}$ | $-0.006^{***}$ | $-0.006^{***}$ |
| | (0.0002) | (0.0002) | (0.001) | (0.001) | (0.001) | (0.001) |
| Primary Schools per 1000 | $-0.214^{***}$ | $-0.214^{***}$ | $-1.514^{***}$ | $-1.513^{***}$ | $-1.684^{***}$ | $-1.677^{***}$ |
| | (0.044) | (0.044) | (0.300) | (0.300) | (0.195) | (0.195) |
| Percent paved roads | $0.002^{***}$ | $0.002^{***}$ | $0.014^{***}$ | $0.014^{***}$ | $0.019^{***}$ | $0.019^{***}$ |
| | (0.001) | (0.001) | (0.004) | (0.004) | (0.003) | (0.003) |
| Constant | $0.548^{***}$ | $0.547^{***}$ | 1.070 | 1.061 | 0.479 | 0.470 |
| | (0.112) | (0.113) | (0.701) | (0.702) | (0.450) | (0.451) |
| Observations | 993 | 993 | 993 | 993 | 993 | 993 |
| $R^2$ | 0.069 | 0.069 | | | | |
| Adjusted $R^2$ | 0.064 | 0.063 | | | | |
| Log Likelihood | | | −733.888 | −733.614 | −932.034 | −931.165 |
| Akaike Inf. Crit. | | | 1,479.776 | 1,481.229 | 1,876.068 | 1,876.330 |

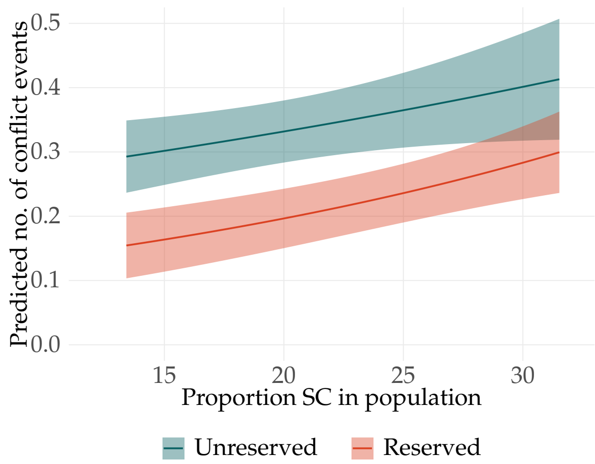
**Note:** Results from regressions of conflict events/fatalities for assemblies. Only caste-related conflict events included (n=3,428). Signficance levels: $^{*}$10%,$^{**}$ 5%,$^{***}$ 1%.




**(a)** Log-linear regression (log(events + 1))




**(b)** Negative binomial regression for events




**(c)** Poisson regression for events

**Figure 7:** Robustness Check: Predicted conflict by reservation status and SC population share, Caste-related conflict only

**Note:** Regressions include main and interaction terms for reservation status and SC population share, and the standard control variables. In all models, standard errors were bootstrapped. The top panel reproduces the log-linear regression from the main specification. The middle panel reports results for zero-inflated negative binomial, the bottom panel for zero-inflated poisson regression models. The range of the SC population share corresponds to the 10th and 90th percentile of the sample distribution.

#### A2.1.2 Alternative sample

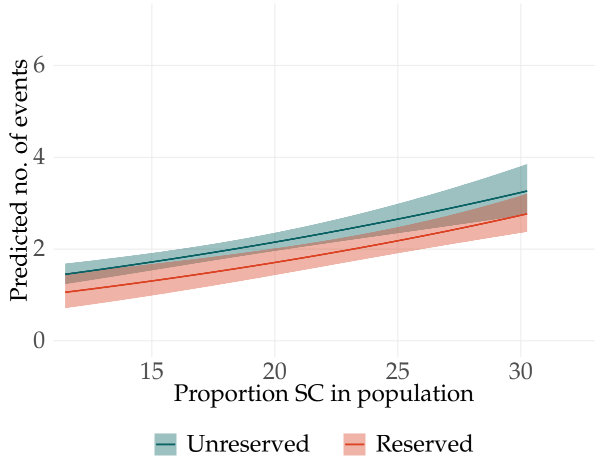
Table 8 shows results from log-linear OLS and negative binomial regressions with an alternative sample: All constituencies in a district whose SC population share is within a 5 percentage point margin of the SC population share of the cutoff constituency (the last reserved constituency) are included.

In all specifications, reservations are associated with fewer conflict events and fatalities. The difference is signficant at the 10% level for events at the mean SC population share. The coefficient on the interaction term is positive, but not significant in any specification. Figure 8 shows the results graphically.

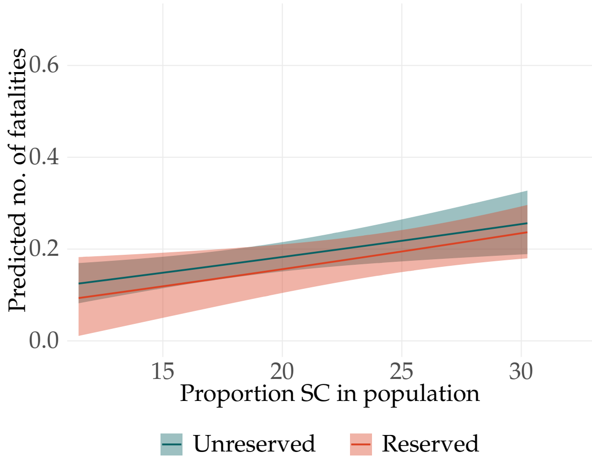
**Table 8:** Robustness Check: Constituency assemblies, alternative sample

| | OLS: log(Events+1) | | OLS: log(Fatalities+1) | | NB: Events | | NB: Fatalities | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Seat reserved for SC** | $-0.145^{**}$ | $-0.150^{**}$ | $-0.021$ | $-0.022$ | $-0.144$ | $-0.178^{*}$ | $-0.214$ | $-0.217$ |
| | (0.061) | (0.063) | (0.026) | (0.027) | (0.092) | (0.095) | (0.189) | (0.198) |
| Percent SC population | $0.228^{***}$ | $0.220^{***}$ | $0.046^{***}$ | $0.044^{***}$ | $0.309^{***}$ | $0.267^{***}$ | $0.236^{***}$ | $0.232^{**}$ |
| | (0.029) | (0.037) | (0.012) | (0.016) | (0.043) | (0.055) | (0.086) | (0.110) |
| **Reserved $\times$ SC pop** | | 0.020 | | 0.005 | | 0.107 | | 0.010 |
| | | (0.058) | | (0.025) | | (0.087) | | (0.177) |
| Population in 1000 | $-0.003^{***}$ | $-0.003^{***}$ | $-0.0001$ | $-0.0001$ | $-0.006^{***}$ | $-0.006^{***}$ | $-0.001$ | $-0.001$ |
| | (0.0004) | (0.0004) | (0.0002) | (0.0002) | (0.001) | (0.001) | (0.001) | (0.001) |
| Primary Schools per 1000 | $-0.557^{***}$ | $-0.556^{***}$ | $-0.206^{***}$ | $-0.206^{***}$ | $-1.008^{***}$ | $-0.999^{***}$ | $-1.918^{***}$ | $-1.918^{***}$ |
| | (0.081) | (0.081) | (0.035) | (0.035) | (0.125) | (0.124) | (0.303) | (0.304) |
| Percent paved roads | $0.005^{***}$ | $0.005^{***}$ | $-0.002^{***}$ | $-0.002^{***}$ | $0.004^{*}$ | $0.004^{*}$ | $-0.019^{***}$ | $-0.019^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.004) | (0.004) |
| Constant | $2.167^{***}$ | $2.163^{***}$ | $0.554^{***}$ | $0.553^{***}$ | $3.644^{***}$ | $3.615^{***}$ | $2.040^{***}$ | $2.038^{***}$ |
| | (0.207) | (0.208) | (0.088) | (0.088) | (0.317) | (0.317) | (0.642) | (0.644) |
| Observations | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 |
| $R^2$ | 0.134 | 0.135 | 0.044 | 0.044 | | | | |
| Adjusted $R^2$ | 0.131 | 0.130 | 0.040 | 0.039 | | | | |
| Log Likelihood | | | | | $-3,048.080$ | $-3,047.295$ | $-822.250$ | $-822.248$ |
| Akaike Inf. Crit. | | | | | 6,108.160 | 6,108.590 | 1,656.499 | 1,658.495 |

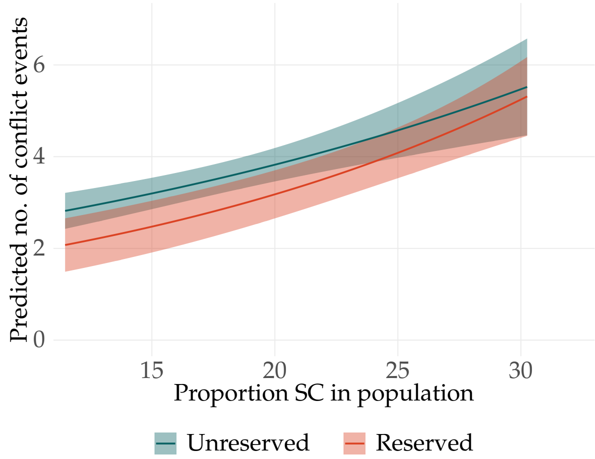
**Note:** Results from regressions of conflict events/fatalities for constituency assemblies.
OLS is for ordinary least squares, NB for negative binomial regression models.
Alternative sample: Constituencies within 5 percentage points SC population margin around cutoff
Signficance levels: $^{*}$10%,$^{**}$ 5%,$^{***}$ 1%.



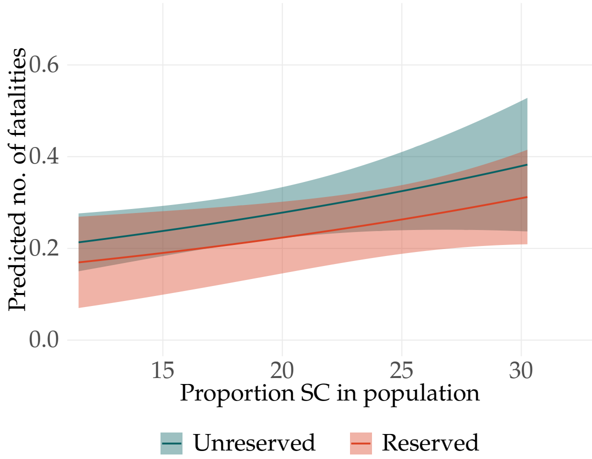

**(a)** Log-linear regression (log(events + 1))



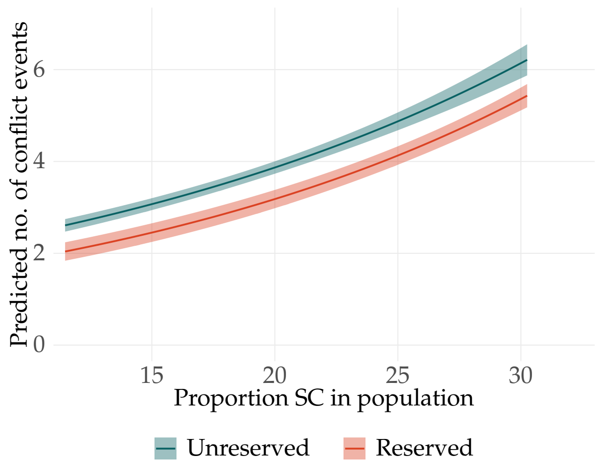

**(b)** Log-linear regression (log(fatalities + 1))



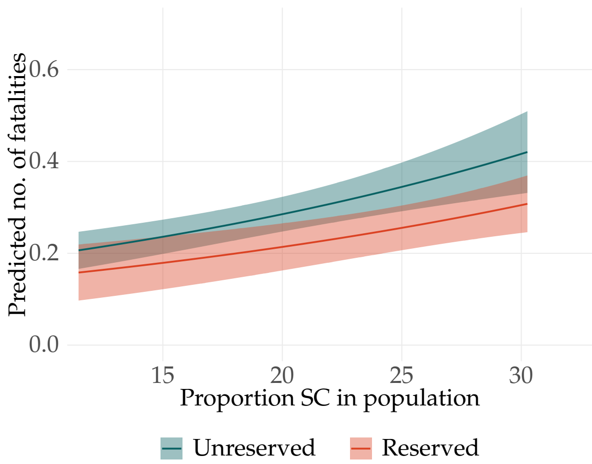

**(c)** Negative binomial regression for events




**(d)** Negative binomial regression for fatalities




**(e)** Poisson regression for events




**(f)** Poisson regression for fatalities

**Figure 8:** Robustness Check: Predicted conflict by reservation status and SC population share, Alternative sample

**Note:** Regressions include main and interaction terms for reservation status and SC population share, and the standard control variables. In all models, standard errors were bootstrapped. The top panel reproduces the log-linear regression from the main specification. The middle panel reports results for zero-inflated negative binomial, the bottom panel for zero-inflated poisson regression models. The range of the SC population share corresponds to the 10th and 90th percentile of the sample distribution.

## A2.2 Villages

Table 10 and Table 9 repeat the village-level analysis but report general heteroskedasticity-robust standard errors. While this does not change the coefficients, the standard errors for the coefficient of interest are substantially narrower: Both in the cross-sectional and in the DiD-specifications, reservations are associated with significantly more conflict (at the 5% level). This should not be interpreted as evidence that reservations increase conflict in villages, but rather show the importance of clustering the standard errors in this setting.

**Table 9:** DiD Estimates: Villages, using robust standard errors

| | Conflict in general | | Conflict between *jatis* | |
|---|---|---|---|---|
| | $\theta = 0$ | $\theta = 1$ | $\theta = 0$ | $\theta = 1$ |
| | (1) | (2) | (3) | (4) |
| **Pradhan seat reserved** | -0.006 | -0.003 | 0.061** | 0.031** |
| | (0.032) | (0.016) | (0.029) | (0.014) |
| Log(Total income) | -0.019 | -0.019 | -0.007 | -0.007 |
| | (0.012) | (0.012) | (0.011) | (0.011) |
| Time trend | -0.201*** | -0.204*** | 0.088*** | 0.118*** |
| | (0.018) | (0.016) | (0.015) | (0.014) |
| Constant | 0.923*** | 0.925*** | 0.482*** | 0.460*** |
| | (0.131) | (0.132) | (0.121) | (0.121) |
| N | 22,482 | 22,482 | 22,476 | 22,476 |
| $R^2$ (within) | 0.04 | 0.04 | 0.02 | 0.02 |
| Mean of DV | 0.62 | 0.62 | 0.46 | 0.46 |

**Note:** Robust standard errors in parentheses.
Significance levels: *10%, **5%, ***1%.

**Table 10:** Results for Villages with robust standard errors

| | Conflict in general | | | | Conflict between *jatis* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Pradhan seat reserved** | 0.017 | -0.134*** | 0.020 | -0.133*** | 0.088*** | -0.040 | 0.096*** | -0.033 |
| | (0.024) | (0.040) | (0.024) | (0.039) | (0.026) | (0.043) | (0.027) | (0.043) |
| Proportion SC population | 0.048 | -0.122** | 0.076 | -0.099* | -0.021 | -0.165*** | -0.019 | -0.166*** |
| | (0.056) | (0.052) | (0.057) | (0.055) | (0.056) | (0.051) | (0.058) | (0.054) |
| **Reserved × SC pop** | | 0.518*** | | 0.524*** | | 0.441*** | | 0.442*** |
| | | (0.098) | | (0.099) | | (0.107) | | (0.108) |
| Respondent from backward caste | | | 0.029 | 0.031 | | | -0.040 | -0.039 |
| | | | (0.026) | (0.025) | | | (0.028) | (0.028) |
| Respondent from forward caste | | | 0.015 | 0.009 | | | -0.009 | -0.014 |
| | | | (0.027) | (0.027) | | | (0.029) | (0.029) |
| Log(Total income) | | | -0.011 | -0.013 | | | -0.014 | -0.016* |
| | | | (0.010) | (0.010) | | | (0.010) | (0.010) |
| N | 11,566 | 11,566 | 11,375 | 11,375 | 11,560 | 11,560 | 11,369 | 11,369 |
| $R^2$ | 0.12 | 0.12 | 0.12 | 0.13 | 0.11 | 0.11 | 0.11 | 0.11 |
| Mean of DV | | | | | | | | |
| Village level controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual level controls | | | ✓ | ✓ | | | ✓ | ✓ |
| State dummies | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

**Note:** Robust standard errors in parentheses. Village level controls: Muslim share of population, Scheduled Tribe share of population, Number of primary and middle schools, connectivity by road. Individual level controls: Caste classification, log(Income), years of education. Significance levels: *10%, **5%, ***1%

## A3 Simulation

In this section, I present Monte-Carlo-simulations confirming the possibility to estimate DiD-regressions despite the missing information on reservation status in 2005. As described in the main text, it is known with certainty that reserved villages in 2011 were not reserved in 2005. However, the reservation status of unreserved villages in 2011 is unknown in 2005. This setting is similar to the estimation of Intent-to-Treat-Effects, but the lack of information on who was initially treated generates some additional complexities. I propose to estimate two DiD-specifications, one under the assumption that all these villages were unreserved in 2005 as well ($\theta = 0$), and one under the assumption that all these villages were reserved in 2005 ($\theta = 1$). If the proportion of reserved villages in 2005 is known and the probability of reservation is uniform across villages, I also propose a linear combination of the two estimates that recovers, on average, the true DiD-estimate.

Figure 9 shows the results from a Monte-Carlo simulation with 10,000 repetitions. I perform the simulations using a randomly generated dataset with observations on 1,000 units over two time periods, a positive time trend, and a positive treatment effect with some idiosyncratic heterogeneity. I use different "cutoff" values, corresponding to different shares of villages reserved in the first and second period.

I first simulate the regressions with the full information on treatment status in both periods to get the full-information DiD estimate. The distribution of these is shown in the red-coloured histograms. I then remove the treatment information for the first period and estimate the two sets of DiD estimates ($\theta = 0$, blue histograms and $\theta = 1$, yellow histograms). As visible from the left panels of Figure 9, the full-information DiD estimate lies strictly between these two: This indicates that (1) the two cases can be used as upper and lower bounds on the full-information DiD, and that (2) a linear combination of the two may recover the full-information DiD estimate.

In the right panels of Figure 9, I compare the full-information DiD estimate to an estimator that reweights the "all-treated" and "none-treated" estimates:

$$\widehat{\beta}_{RW} = \frac{1-\pi_t}{1+\pi_t} \cdot \widehat{\beta}_{\theta 0} + \frac{2\pi_t}{1+\pi_t} \cdot \widehat{\beta}_{\theta 1}$$

$\pi_t$ denotes the fraction of observations that were treated in the first period among those not treated in the second period. , $\widehat{\beta}_{\theta 0}$ is the DiD estimate assuming that $\theta = 0$, and $\widehat{\beta}_{\theta 1}$ the DiD estimate assuming that $\theta = 1$. As the $\pi_t$ goes to zero, $\widehat{\beta}_{RW}$ corresponds to $\widehat{\beta}_{\theta 0}$. As the $\pi_t$ goes to one, $\widehat{\beta}_{RW}$ corresponds to $\widehat{\beta}_{\theta 1}$. The 'weight' on $\widehat{\beta}_{\theta 1}$ is double, as any additional village that gets treated has a double effect: it is removed from the control group and added to the treatment group, and therefore has to be counted twice. The dark green histograms on the right panel show the distribution of the reweighted estimator. While its variance is slightly larger than the full-information estimator, the weighted estimate recovers the true effect on average.

In addition, here unreported results of the simulation show that the standard error is proportional to the estimated coefficient, such that the t-statistic and p-value on the coefficient are independent on the weights in the reweighting estimator.

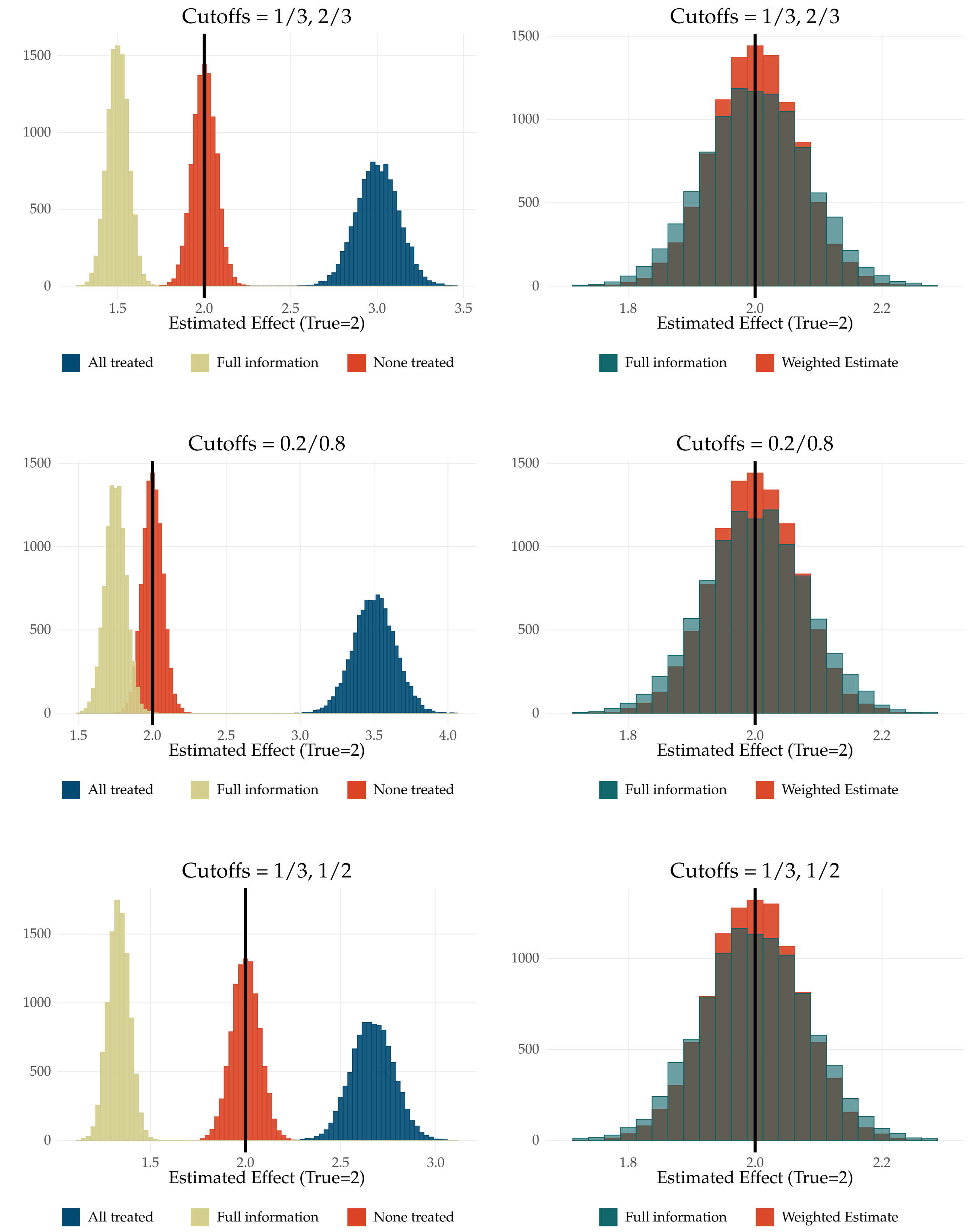



**Figure 9:** Results for Monte-Carlo simulated DiD estimates

**Note:** The subfigures show DiD estimates from 10,000 Monte-Carlo simulations with 1,000 observed units over two time periods. Some units are never treated (proportion: first cutoff), some are treated in period 1 but not in 2 (second – first cutoff) and some in period 2 but not in 1 (1 – second cutoff). Red histograms show the distribution of DiD estimates under full information. In the other cases, it is unknown which of the units untreated in period 2 were treated in period 1. For yellow, calculations were performed assuming $\theta = 1$. For blue, I assumed $\theta = 0$. Dark green histograms show estimates under the proposed reweighing of the latter two.

# A4 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”.

In appendix A2.1.1, I only include events for which the accompanying note in the ACLED data set contains one of the following strings: `caste`, `schedule`, `brahmin`, `untouch`, `forward`, `obc`, `dalit`, `reserv`, `jat`, `jaat`, `" sc "`, `(sc)`, `discrim`, `category`. This filter therefore proxies the intensity of conflict related to communal tensions related to caste. Applying this filter reduces number of conflict events from 59,996 to 3,428. As there are only 213 associated fatalities, I do not report results on these.