ONLINE APPENDIX

Political Competition Over Life and Death
– Infant Mortality and Social Provision in India

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Appendix A A Model of Political Competition

With resources x, the incumbent chooses the level of social provision $p \leq x$ as a public good. The opportunity cost net of social benefits of providing p is ap. Among the gains (not subtracted from the net opportunity costs in a) are improvements in the chance of being reelected. The probability that the incumbent wins the election is

$$s = \frac{g}{g+k} \tag{A.1}$$

where we capture how the relative contest efforts – g by the incumbent and k by the challenger – influence the uncertain outcome of the election. The value of s is thus the expected probability that the incumbent wins. A higher level of p is supposed to raise $g = g(p)$, which is increasing and concave. We use $g(p) = p^{\theta}$ with $\theta \leq 1$ in the exposition.

As discussed in Section II, the incumbent's opportunity costs per unit of p will likely increase with local income inequality. The challenger, in contrast, must use campaigning to increase k in (A.1) at a unit costs b to improve his chance to win $(1 - s)$.

The pay-off of being (re)elected is a given value, V, for both the incumbent and the challenger. Before the election, the expected pay-offs (net of discounting) are V_I to the incumbent and V_C to the challenger given by

$$V_I = sV - ap \tag{A.2}$$

$$V_C = (1-s)V - bk \tag{A.3}$$

The solution for the incumbent's social provision (our main interest) is

$$p = \min[p^*, x] \tag{A.4}$$

where p^* is the interior Nash-equilibrium of the (simultaneous-move) game where the incumbent chooses p to maximize V_I, and the challenger chooses k to maximize V_C. The first order conditions are $[kg'(p)/(g+k)^2]V - a = 0$ for p and $[g/(g+k)^2)]V - b = 0$ for

for k. Using (A.1), the two conditions can be written as

$$p^* = \frac{s(1-s)\theta}{a} V \tag{A.5}$$

$$k^* = \frac{s(1-s)}{b} V \tag{A.6}$$

From (A.5) and (A.6) we get

$$k = \frac{a}{b\theta} p \tag{A.7}$$

Inserting this in (A.5), the interior $p = p^*$ must satisfy the equation

$$V = bp^\theta + 2pa/\theta + (a/\theta)^2 (1/b) p^{2-\theta} \equiv H(p, a, b) \tag{A.8}$$

Let H_i indicate the partial derivative of H with respect to $i = p, a, b$. It is straightforward to check that both H_p and H_a are positive, implying (because the left-hand side is given):

$$\frac{dp}{da} = -\frac{H_a}{H_p} < 0 \tag{A.9}$$

and hence the following result:

Result 1: *The interior level of p is declining in a.*

We next fix a. Which level of b maximizes social provision p? From (A.8) we have

$$\frac{dp}{db} = -\frac{H_b}{H_p} \tag{A.10}$$

Since $d^2p/(dp)^2 < 0$, the solution to $H_b = 0$ maximizes p. From (A.8) (after some rearranging) we find

$$H_b = -p^\theta[(1 - \frac{a}{b\theta}p^{1-\theta})(1 + \frac{a}{b\theta}p^{1-,\theta})] \tag{A.11}$$

which demonstrates that

$$b = \frac{a}{\theta}p^{1-\theta} \tag{A.12}$$

maximizes p. Inserting (A.7) in (A.1), we have $s = p^\theta/[p^\theta + pa/(b\theta)]$ for the optimal $p = p^*$. Inserting (A.12) in this expression of s we get $s = 1/2$ and our second result:

Result 2: *The level of political competition that maximizes p has* $s = 1/2$.

A.1 The Special Case with $\theta = 1$

Results 1 and 2 are even more transparent in the special case of $\theta = 1$. From (A.8) we then get an explicit solution:

$$p = \frac{b}{(a+b)^2}V \tag{A.13}$$

where we can easily check that p, for any a, is maximized for $b = a$. Using $k = (a/b)p$ from (A.7) in (A.1) we have

$$s = \frac{b}{a+b} \tag{A.14}$$

confirming that p is maximal for $s = 1/2$.

A.2 The Link Between p and Political Competition, $s(1-s)$

Results 1 and 2 together with (A.5) demonstrate the link between p^* and $s(1-s)$. This measure of political competition is proportional to one minus the Herfindahl-Hirschman index, as $1 - (s^2 + (1-s)^2) = 2s(1-s)$ – the main index in our empirical exploration. The higher the level of this measure of political competition, the higher the value of p^*.

When the levels of $a \approx b$ are low enough, $p^* > x$ (and hence $p = x$). At this point the incumbent's marginal benefit of social provision outweighs the marginal costs, $s(1-s)V/x > a$ with $k = \sqrt{x^\theta V/b} - x^\theta$ and $s = x^\theta/(x^\theta + k) = x^{\theta/2}/\sqrt{V/b}$. Accordingly, changes in a have no effect: $dp/da = 0$. For a given x, this constrained case arises when $s(1-s)$ is high, and a and b are low. Sufficient conditions are $s = 1/2$ and $x < V/(4a)$.

Appendix B A Politically Neutral Redistricting

The delimitation impacted almost all constituencies in large states. Most post-delimitation constituencies were, therefore, new. For the analysis in this section, we define the corresponding post-delimitation constituency as the one with the largest overlap in voters with the pre-delimitation constituency. As such, being "redistricted" means that one lives in a post-delimitation constituency where most voters differ from those in one's pre-delimitation constituency.

Based on this notion, about one-quarter of the rural voters were allocated to a new constituency. Table B1 displays these statistics for the 15 states in our analysis, along with the number of constituencies per state and the average number of voters per constituency.

Table B1: Changes in parliamentary constituencies

	Number of constituencies (1)	Number of voters per constituency (in million) (2)	Average share of voters allocated to a new constituency (3)
Andhra Pradesh	42	1.35	.26
Bihar	40	1.37	.29
Chhattisgarh	11	1.41	.14
Gujarat	26	1.41	.21
Haryana	10	1.21	.16
Karnataka	28	1.45	.17
Kerala	20	1.10	.32
Madhya Pradesh	29	1.32	.15
Maharashtra	42	1.49	.26
Odisha	21	1.29	.16
Punjab	13	1.30	.30
Rajasthan	25	1.48	.26
Tamil Nadu	38	1.07	.30
Uttar Pradesh	80	1.46	.30
West Bengal	40	1.25	.25
All	465	1.35	.25

The estimates are based on our own calculations using digitalized maps. The number of PCs in the table does not always correspond to the actual number of PCs, as we have excluded PCs that are all urban. The number of voters in Column 2 refers to the reported electorate as of 2009.

The remainder of this section investigates whether the redistricting was politically neutral. Many countries go through redistricting processes, and influential politicians are often accused of tweaking the boundary changes to create safer seats for themselves.

Despite the independent Delimitation Commission, we cannot exclude the possibility that something similar happened in India.

Iyer and Reddy (2013) study the redistricting of State Assembly constituencies in two large states, Andhra Pradesh and Rajasthan, and conclude that the boundary changes "were politically neutral for most parts". Bardhan et al. (2020) study the boundary changes in West Bengal and come to the same conclusion. We conduct a similar analysis as Iyer and Reddy (2013) for the parliamentary constituencies (as opposed to state assembly constituencies) for the 15 states included in our main analysis.

We first examine the extent of redistricting. Because the boundary changes aimed to equalize population sizes within states, we expect the highest absolute population changes in small and large constituencies, that is we expect a U-shaped relationship between the original population sizes and the changes in the number of people within constituencies. Table B2 displays our test of this relationship, using the same set of constituency level controls as Iyer and Reddy (2013): The population share of Scheduled Castes (SCs), Scheduled Tribes (STs), males, literates and people in rural areas. Column 2 also includes state fixed effects. There is a clear U-shaped relationship, which suggests the redistricting was done in the intended direction.

Table B2: Initial population and absolute population changes

	(1)	(2)
Eligible voters pre-delimitation	-.807***	-.919***
	(.156)	(.194)
Eligible voters pre-delimitation squared	.248***	.269***
	(.052)	(.063)
Observations	465	465
State FEs	No	Yes

The regressions include controls for the population share of SCs, STs, males, literates and people in rural areas. The regression in Column 2 also includes state fixed effects. Robust standard errors are shown in parentheses. *** significant at 1 percent.

Next, we look for signs of political interference in the redistricting process. It is difficult to find such signs using post-delimitation political outcomes, as those may be affected by other factors. Therefore, we focus on ex-ante aspects likely to affect electoral prospects, such as the political campaigning costs. Following Iyer and Reddy (2013), we construct five variables intended to capture changes in these costs:

i) The percentage increase in the number of eligible voters (we code a decrease as zero),

ii) The fraction of old voters that remained in the constituency,

iii) Whether the constituency got reserved for SCs,

iv) Whether the constituency got reserved for STs,

v) The demographical changes of the constituency, captured by $\sum_j (D_{j,old} - D_{j,new})^2$, where $D_{j,old}$ is an index measuring the demographic characteristic j for the pre-delimitation constituency, and $D_{j,new}$ for the post-delimitation constituency. We construct the index for the set of control variables included in Table B2: The population share of SCs, STs, males, literates and people in rural areas.

Suppose influential politicians were able to affect the process. In that case, we expect their constituencies to have smaller increases in population, larger shares of old voters in the new constituencies, fewer changes in the reservation status and smaller changes in voter demographics. We now have to define the "influential" politicians, that is individuals we suspect could have been in a position to influence the process. We construct four binary variables denoting the following type of MPs: i) those that served as associate members of the Delimitation Commission (as they directly had the opportunity to advice the commission), ii and iii) those that served as either Cabinet or State Ministers of the ruling (national) government at the time of the Delimitation, and iv) those that represented the same political party as the local state government at the time of the Delimitation.

We regress each variable that captures the change in campaigning costs on the variables denoting influential MPs. Table B3 presents the results. Overall, we find that the politician-level variables have limited prediction power of the constituency-level variables. The bottom row in the table displays the joint p-value, which is above conventional significance levels in all regressions. Some individual coefficients are significantly different from zero, though: MPs representing the same political party as the state government were less likely to have their constituency reserved for SCs, but also kept a smaller share of their old voters.

In sum, we interpret these results as support for the notion of a "politically neutral redistricting", as we do not find any clear indications of (ex-ante) improved electoral prospects for the most prominent incumbent politicians.

Table B3: Redistricting and electoral prospects (2004)

	Increase in voters (%) (1)	Old voters (%) (2)	Got reserved for SCs (3)	Got reserved for STs (4)	Demographic change (5)
Member of Delimitation Commission	-.001	.002	-.012	.015	-.000
	(.011)	(.020)	(.048)	(.022)	(.002)
Cabinet Minister	-.010	.014	.065	-.028	.007
	(.019)	(.044)	(.094)	(.032)	(.006)
State Minister	-.004	-.051	-.086*	-.042	.001
	(.017)	(.031)	(.051)	(.027)	(.004)
From same party as state government	.013	-.046**	-.074**	-.008	.001
	(.009)	(.018)	(.035)	(.017)	(.002)
Observations	465	465	465	465	465
Joint p-value	.636	.069	.091	.504	.817

All regressions control for the population of the constituency and its square, the population share of SCs, STs, males, literates and people in rural areas, as well as state fixed effects. Robust standard errors are shown in parentheses. * significant at 10 percent, ** significant at 5 percent.

Appendix C Robustness Checks

In this section, we test the robustness of our main results to the exclusion of Muslim children; the inclusion of controls for political parties and the reservation status, and restricting the sample to observations within a certain distance from the closest post-delimitation constituency. Finally, we also show that our results are unlikely to be driven by imbalances at administrative levels lower than the districts.

C.1 Excluding Muslim Children

Table C1 shows that the results for post-neonatal infant mortality are robust to the exclusion of Muslim children (about 10% of the sample). We conduct this robustness check because there is a minor imbalance in religion (see Table D1), and Geruso and Spears (2018) show that Muslim children are more likely to survive their first year of life than Hindu children.

Table C1: Post-Neonatal infant mortality, excluding muslims

	Post-Neonatal infant mortality	
	(1)	(2)
Inequality	.0005	.0002
	(.0017)	(.0017)
Political competition	-.0004	-.0001
	(.0016)	(.0017)
Inequality ×	-.0020*	-.0021*
Political competition	(.0012)	(.0012)
Observations	80,967	80,967
Average expenditures	Yes	Yes
Controls	No	Yes
Unit	Infant	Infant

The independent variables are standardized, and the coefficients thus reflect the impact at average levels. Both columns include pre-delimitation constituency × district × birth year fixed effects and control for average expenditures. Column 2 also controls for area and child level characteristics. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses. * significant at 10 percent.

C.2 Including Political Parties and the Reservation Status

Table C2 provides two additional robustness checks. First, we test whether variation in the MPs' political parties drives the results rather than political competition. In Column 1, we add five binary variables that denote the largest political parties in 2009 (INC, BJP, SP, JD(U), and BSP); in Column 2, we interact these binary variables with inequality and political competition. All the results are robust, except the impact on the healthcare index in Column 2. Second, we conduct a similar exercise by adding binary variables denoting whether constituencies were reserved for SCs or STs. Columns 3-4 show the results are robust to these specifications.

Table C2: Including political parties and the reservation status

	Political party dummies		Reservation status	
	(1)	(2)	(3)	(4)
Panel A: Post-Neonatal infant mortality (N=90,236):				
Inequality	.0000	.0028	-.0000	.0004
	(.0016)	(.0020)	(.0015)	(.0018)
Political competition	.0011	.0000	.0009	.0011
	(.0016)	(.0022)	(.0016)	(.0017)
Inequality ×	-.0020**	-.0016*	-.0020**	-.0020**
Political competition	(.0010)	(.0008)	(.0009)	(.0009)
Panel B: Healthcare (N=5,679):				
Inequality	-.0804	-.0771	-.0673	-.0181
	(.0547)	(.0721)	(.0558)	(.0558)
Political competition	.0051	-.0560	.0117	-.0128
	(.0488)	(.1077)	(.0519)	(.0484)
Inequality ×	.0625*	.0196	.0883**	.0879***
Political competition	(.0345)	(.0395)	(.0367)	(.0329)
Panel C: MGNREGA (N=451,231):				
Inequality	-.0172*	-.0105	-.0187*	-.0153
	(.0100)	(.0235)	(.0099)	(.0104)
Political competition	-.0031	-.0039	-.0033	-.0006
	(.0096)	(.0149)	(.0092)	(.0090)
Inequality ×	.0113*	.0111*	.0110*	.0104*
Political competition	(.0062)	(.0067)	(.0060)	(.0059)
Full set of interactions	No	Yes	No	Yes

The independent variables are standardized, and the coefficients thus reflect the impact at average levels. The regressions control for average expenditures and area characteristics. In Panel A, we control for child characteristics as well. Panel A includes pre-delimitation constituency × district × birth year fixed effects, Panel B pre-delimitation constituency × district fixed effects, and Panel C pre-delimitation constituency × district × fiscal year fixed effects. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses. *** significant at 1 percent, ** significant at 5 percent * significant at 10 percent.

C.3 Restricting the Distance to Constituency Borders

We now restrict the sample to observations with a maximum distance of 40 or 20 kilometres to their closest post-delimitation constituency border. Table C3 shows we lose some precision, but the results are otherwise robust to this sample selection. In addition, we also present a specification for the mortality sample in which we remove observations closer than five kilometres from their closest constituency border (Column 3). This exercise is motivated by the rural clusters in the NFHS being randomly displaced with up to five kilometers.[1] The interaction effect is larger in absolute size in this sample.

Table C3: Restricting the distance to the closest post-delimitation constituency border

	Post-neonatal infant mortality			Healthcare index		MGNREGA disbursement	
	≤40km (1)	≤20km (2)	>5km (3)	≤40km (4)	≤20km (5)	≤40km (6)	≤20km (7)
Inequality	-.0003 (.0015)	-.0005 (.0017)	-.0004 (.0023)	-.0809 (.0595)	-.0609 (.0583)	-.0135 (.0119)	-.0113 (.0136)
Political competition	.0008 (.0016)	.0010 (.0018)	.0032 (.0026)	.0372 (.0527)	.0356 (.0545)	-.0053 (.0111)	-.0080 (.0122)
Inequality × Political competition	-.0019** (.0009)	-.0017* (.0009)	-.0029** (.0015)	.0792** (.0365)	.0723* (.0395)	.0098 (.0077)	.0102 (.0083)
Observations	89,345	81,535	55,541	5,195	4,728	387,334	350,692
Average expenditures	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unit	Infant	Infant	Infant	PHC	PHC	GPs	GPs

See Table 4 for a description of the independent variables and controls. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses. ** significant at 5 percent, * significant at 10 percent.

C.4 Public Good Provision at Political Levels below the District

Our main specification includes fixed effects for pre-delimitation constituencies interacted with districts. As outlined in the paper, including districts is crucial, as it is the most important administrative unit for social provision to the poor. Politicians and bureaucrats at lower levels, such as blocks and assembly constituencies (ACs), may also influence local

[1] An additional 1% of the NFHS clusters is displaced with a maximum of ten kilometres.

public goods provision. There can be substantial variation across blocks and ACs, but – given that these map entirely into one district – the concern is whether there is balance, that is whether the different treatment areas are balanced on relevant block and AC characteristics.

We test whether the three samples (post-neonatal infant mortality, healthcare and MGNREGA) are balanced in terms of (i) being redistricted at the AC level and (ii) being in a "split" block, that is a block that overlaps with more than one AC. The latter is motivated by Gulzar and Pasquale (2017), who show that there is less MGNREGA provision in split blocks and explain this as follows, *"[...] politicians face strong incentives to motivate bureaucrats to improve the implementation of local development schemes [...] when they can internalize the electoral benefits of doing so."* (Gulzar and Pasquale, 2017, p.163). Table C4 presents the results for both our balancing checks: We check for differences between households, PHCs and GPs allocated to new constituencies and those that remain in their original ones, and we regress our main specification using the new dummies as dependent variables. For the MGNREGA sample, locations that were redistricted at the PC level were slightly more likely to be redistricted also at the AC level. There are no differences in the likelihood of being in a split block. For the mortality sample, there is a positive association between the interaction term and being located in a split block.

These sample imbalances are minor, but we still test whether our main results are robust to omitting areas redistricted at the AC level or located in a split block. Table C5 shows our main conclusions do not change, implying that the sample imbalances do not drive the results. We, therefore, conclude that our results are unlikely to be driven by imbalances in administrative levels lower than the districts.

Table C4: Balance of redistricting at the AC-level and splitted blocks

	Redistricted at the AC-level		Splitted block	
	(1)	(2)	(3)	(4)
Panel A: Post-neonatal infant mortality (N=90,236):				
Redistricted at the PC-level	.0122		.0110	
	(.0300)		(.0214)	
Inequality		.0156		-.0033
		(.0180)		(.0151)
Political competition		-.0002		-.0031
		(.0224)		(.0188)
Inequality ×		.0290		.0310**
Political competition		(.0178)		(.0154)
Panel B: Healthcare (N=5,679):				
Redistricted at the PC-level	.0241		-.0035	
	(.0250)		(.0278)	
Inequality		.0151		-.0223
		(.0195)		(.0234)
Political competition		.0146		.0184
		(.0238)		(.0278)
Inequality ×		.0215		.0317
Political competition		(.0182)		(.0208)
Panel C: MGNREGA (N=150,413):				
Redistricted at the PC-level	.0572**		-.0079	
	(.0241)		(.0241)	
Inequality		-.0021		-.0065
		(.0205)		(.0177)
Political competition		-.0056		.0284
		(.0263)		(.0322)
Inequality ×		.0240		.0218
Political competition		(.0159)		(.0178)

The outcome variable in Columns 1-2 takes value one if the location was redistricted at the AC-level, and in Columns 3-4 if the location is in a splitted block. Inequality and political competition are standardized and the coefficients thus reflect the impact at average levels. The regressions control for average expenditures and area characteristics. In Panel A, we control for child characteristics as well. Panel A includes pre-delimitation constituency × district × birth year fixed effects, Panel B pre-delimitation constituency × district fixed effects, and Panel C pre-delimitation constituency × district × fiscal year fixed effects. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses. ** significant at 5 percent.

TABLE C5: Excluding locations redistricted at the AC level or in a split block

	Post-neonatal infant mortality		Healthcare index		NREGA disbursements	
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality	.0011	-.0001	.0096	-.0357	-.0304**	-.0296***
	(.0019)	(.0018)	(.0592)	(.0693)	(.0136)	(.0115)
Political competition	.0007	.0003	-.0316	.0356	.0001	.0154
	(.0022)	(.0020)	(.0544)	(.0605)	(.0108)	(.0099)
Inequality	-.0021**	-.0021**	.0832**	.0844*	.0133*	.0117*
Political competition	(.0009)	(.0009)	(.0353)	(.0463)	(.0080)	(.0070)
Observations	52,873	66,256	4,088	4,073	319,863	319,962
Average expenditures	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Unit	Infant	Infant	PHC	PHC	GPs	GPs
Remove AC-redistricted	Yes	No	Yes	No	Yes	No
Remove split blocks	No	Yes	No	Yes	No	Yes

The uneven columns remove observations from locations that were redistricted at the state assembly level, and the even numbered columns remove observations location in blocks that overlap with more than one state assembly constituency. The independent variables are standardized, and the coefficients thus reflect the impact at average levels. Columns 1-2 include pre-delimitation constituency × district × birth year fixed effects, Columns 3-4 pre-delimitation constituency × district fixed effects, and Columns 5-6 pre-delimitation constituency × district × fiscal year fixed effects. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Appendix D Other Results

We present several additional results. First, we graphically present the distribution of inequality and political competition across constituencies in India before providing some additional balance tests. Next, we show the effects on neonatal infant mortality and the sub-indices of our health index. Finally, we discuss other outcome variables: employment, firms and night-time light.

D.1 Distribution of Inequality and Political Competition

Figure D1 plots the correlation between political competition in 2004 and 2009, as measured by one minus the Herfindahl-Hirschman index. As in our analysis, each post-delimitation constituency is matched to the pre-delimitation constituency with the largest population overlap. The correlation is relatively high (.51).

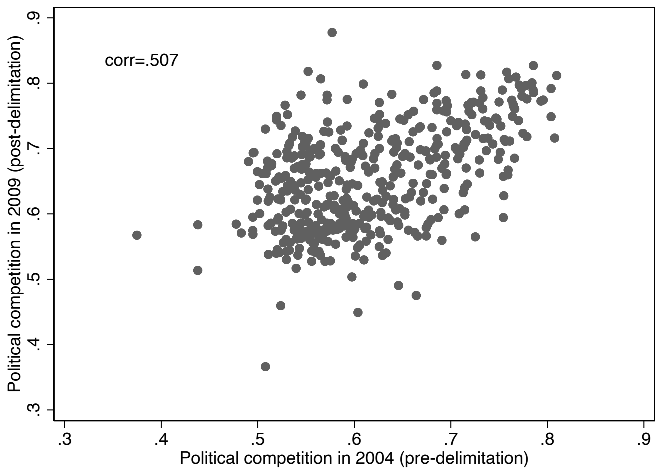

FIGURE D1: Political competition in 2004 versus 2009
Note: The figure plots political competition (measured by one minus the Herfindahl-Hirschman index) in 2004 (pre-delimitation) versus 2009 (post-delimitation).

Figure D2 maps inequality and political competition across pre-delimitation constituencies in India. As in our main specifications, we measure political competition as one minus the Herfindahl-Hirschman index and inequality using the Gini coefficient for household expenditures. The correlation between the two measures is relatively low (-.1).

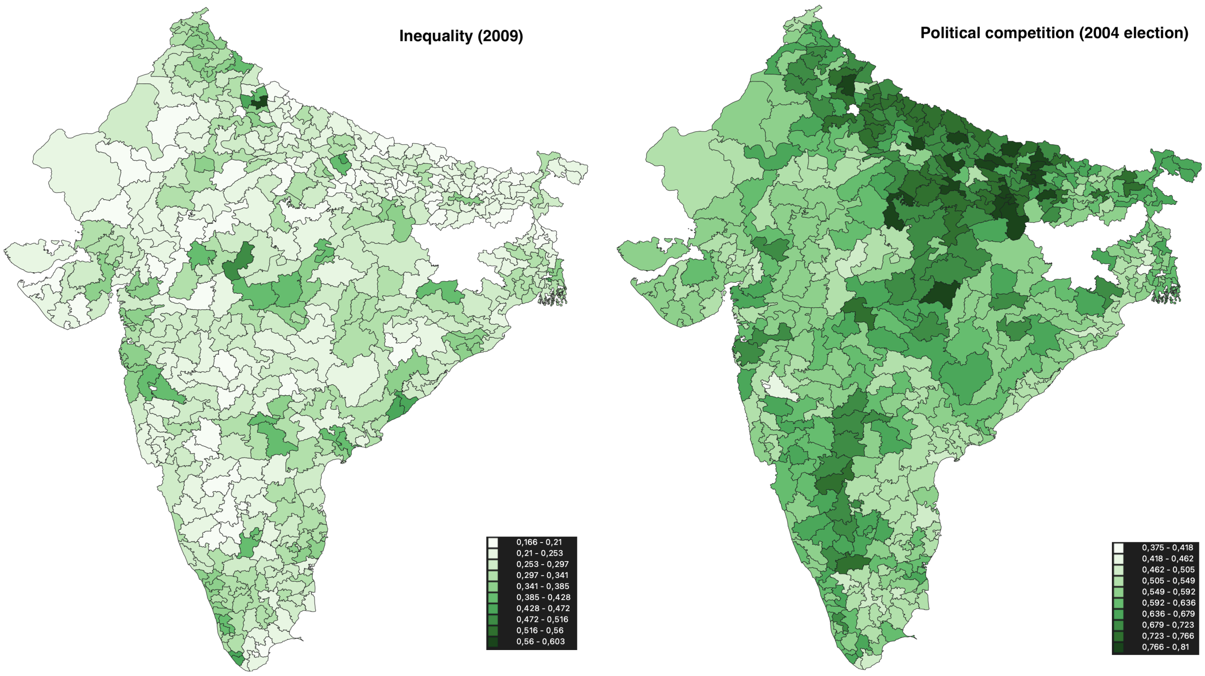

FIGURE D2: Mapping inequality and political competition

Note: The left panel plots inequality (measured by the Gini coefficient), and the right panel political competition (measured by one minus the Herfindahl-Hirschman index) across pre-delimitation constituencies. Darker colors are associated with higher values of inequality and political competition.

D.2 Balancing Tests

Table D1 displays a balancing test where we regress our main specifications (Equations 1, 2 and 3), using the area and individual controls as dependent variables. The results suggest that, apart from religion, our variables of interest cannot predict the area and individual controls.

Table D1: Balance table

	Mortality sample (N=90,236)			Healthcare sample (N=5,679)			MGNREGA sample (N= 451,231)		
	Inequality	Political competition	Interaction	Inequality	Political competition	Interaction	Inequality	Political competition	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share of Scheduled Castes	-.0015	-.0018	.0011	.0029	-.0001	-.0052**	-.0015	-.0000	.0019
	(.0027)	(.0035)	(.0020)	(.0035)	(.0040)	(.0025)	(.0024)	(.0044)	(.0020)
Share of Scheduled Tribes	.0059	.0160***	-.0010	-.0029	.0163**	.0050	-.0029	-.0021	.0076*
	(.0052)	(.0062)	(.0034)	(.0080)	(.0071)	(.0059)	(.0085)	(.0085)	(.0046)
Share of children below 6 years old	.0015**	-.0005	.0004	.0010*	.0001	.0002	.0015**	-.0010	-.0002
	(.0006)	(.0010)	(.0006)	(.0006)	(.0008)	(.0005)	(.0006)	(.0008)	(.0004)
Share of literate people	-.0065*	-.0001	-.0012	-.0057	-.0014	.0004	-.0048	.0033	-.0019
	(.0037)	(.0043)	(.0020)	(.0038)	(.0030)	(.0025)	(.0035)	(.0043)	(.0021)
Share of villages with a primary school	.0034	.0043	-.0002	.0086	.0044	-.0008	.0073	-.0094	.0041
	(.0060)	(.0072)	(.0041)	(.0071)	(.0069)	(.0051)	(.0045)	(.0066)	(.0033)
Share of villages with a PHC	-.0001	-.0002	-.0005	.0006	.0014	-.0001	.0021	.0032	-.0008
	(.0015)	(.0016)	(.0007)	(.0025)	(.0020)	(.0018)	(.0020)	(.0020)	(.0014)
Share of villages with a PHC sub-centre	.0075	-.0022	-.0020	.0079	.0025	.0010	.0075*	-.0040	.0007
	(.0046)	(.0048)	(.0029)	(.0062)	(.0062)	(.0045)	(.0042)	(.0048)	(.0027)
Share of villages with tap water	-.0073	.0038	.0011	-.0053	.0101	-.0001	-.0121	.0256**	-.0082
	(.0089)	(.0088)	(.0075)	(.0088)	(.0111)	(.0077)	(.0115)	(.0123)	(.0073)
Share of villages with electricity	.0084	.0130	.0007	.0045	.0129	.0060	.0005	.0062	.0051
	(.0092)	(.0156)	(.0059)	(.0110)	(.0102)	(.0081)	(.0080)	(.0115)	(.0058)
Share of villages with paved road	.0013	.0010	-.0011	.0033	-.0082	.0000	.0047	-.0046	.0006
	(.0055)	(.0080)	(.0039)	(.0105)	(.0096)	(.0091)	(.0065)	(.0087)	(.0052)
Child is a girl	-.0020	-.0014	-.0050						
	(.0039)	(.0057)	(.0040)						
Child is a twin	-.0005	.0003	.0012						
	(.0011)	(.0019)	(.0012)						
Religion: Hindu	-.0102	.0102	-.0168**						
	(.0065)	(.0097)	(.0065)						
Religion: Muslim	.0125	-.0101	.0198***						
	(.0068)	(.0094)	(.0068)						
Religion: Christian	-.0023	.0017	.0015						
	(.0017)	(.0017)	(.0012)						
Religion: Sikh	-.0002	-.0006	-.0038*						
	(.0042)	(.0016)	(.0023)						
Religion: Buddhist	.0001	.0000	-.0005						
	(.0006)	(.0006)	(.0005)						

Columns 1-3 report the correlation of our key variables of interest with area and child-level characteristics for the mortality sample, Columns 4-6 with area characteristics for the healthcare sample, and Columns 7-9 with area characteristics for the MGNREGA sample. The independent variables are standardized, and the coefficients thus reflect the impact at average levels. The controls are the same as in Table 4. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

D.3 Neonatal Infant Mortality

Table D2 shows estimates for neonatal mortality using baseline specification (1). As discussed in Section IV.C, we distinguish between the two types of mortality as the policies needed to reduce them are very different. Although post-neonatal infant deaths can be reduced through quite simple interventions, the reduction in neonatal deaths depends on the provision of individual clinical care. As such, it is not entirely surprising that we do not find any impact on neonatal mortality. The interaction term is insignificant and small relative to the sample mean.

Table D2: Neonatal infant mortality

	Neonatal infant mortality	
	(1)	(2)
Inequality	.0012	.0010
	(.0021)	(.0023)
Political competition	-.0001	.0003
	(.0020)	(.0021)
Inequality ×	.0014	.0013
Political competition	(.0013)	(.0014)
Observations	116,917	116,917
Average expenditures	Yes	Yes
Controls	No	Yes
Unit	Infant	Infant

The independent variables are standardized, and the coefficients thus reflect the impact at average levels. Both columns include pre-delimitation constituency × district × birth year fixed effects. Column 2 also controls for average expenditures and child and area characteristics. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses.

D.4 Healthcare Sub-Indices and Demand for Healthcare

In Table D3, we present estimates for each variable that comprises our healthcare index. The estimates are based on baseline specification (2). Most of the interaction terms between inequality and political competition are positive, and significantly so for doctor, nurse/midwife, provision of antenatal care, provision of vaccinations, and school health check-ups.

Table D4 displays the estimates for the demand for healthcare we discussed in Sections

V.A and V.B.

Table D3: Regressions on variables that comprise the health index

	Inequality (1)	Political competition (2)	Interaction (3)	Mean dep. variable (4)	Obs. (5)
Panel A: Staff					
Doctor	-.0065	.0033	.0192*	.8260	5,677
	(.0196)	(.0204)	(.0107)		
Nurse/midwife	-.0065	.0034	.0426***	.8450	5,640
	(.0205)	(.0193)	(.0156)		
Health visitor	-.0148	.0149	.0110	.4713	5,646
	(.0271)	(.0238)	(.0169)		
Panel B: Services available					
Provision of antenatal care	.0065	-.0053	.0405**	.7905	5,675
	(.0261)	(.0221)	(.0173)		
Conduct deliveries	.0143	.0003	.0128	.6627	5,675
	(.0243)	(.0234)	(.0159)		
Management of diarrhea	-.0338	.0271	-.0064	.4967	5,674
	(.0295)	(.0290)	(.0160)		
Management of pneumonia	-.0430*	.0057	-.0052	.4043	5,669
	(.0244)	(.0247)	(.0142)		
Provision of vaccinations	-.0077	-.0022	.0300*	.7490	5,646
	(.0260)	(.0226)	(.0163)		
School health check-ups	-.0157	-.0105	.0335**	.3195	5,656
	(.0244)	(.0268)	(.0159)		

Each row presents a separate regression following Equation (2). Columns 1-3 present the coefficients for inequality, political competition and their interaction. These variables are standardized, and the coefficients thus reflect the impact at average levels. Column 4 shows the sample mean of the dependent variable, and Column 5 the number of observations. All regressions control for average expenditures, area characteristics, and pre-delimitation constituency × district fixed effects. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent

Table D4: The demand for healthcare at PHCs

	Household chooses public healthcare	
	NFHS 2015-2016	DLHS 2007-2008
	(1)	(2)
Inequality	.0018	.0102
	(.0079)	(.0100)
Political competition	.0045	.0009
	(.0056)	(.0101)
Inequality ×	.0093***	-.0036
Political competition	(.0031)	(.0063)
Observations	190,197	338,489
Mean dependent variable	.445	.441
Average expenditures	Yes	Yes
Controls	Yes	Yes
Unit	HHs	HHs

The dependent variable takes value one if the household responded "a government healthcare facility" to the following survey question: *When members of your household get sick, where do they generally go for treatment?* The independent variables are standardized, and the coefficients thus reflect the impact at average levels. All regressions control for average expenditures, area and household characteristics, and pre-delimitation constituency × district fixed effects. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses. *** significant at 1 percent.

D.5 Employment, Firms and Night-Time Light

Table D5 presents estimates for three additional economic outcomes. First, we extract information from the Economic Census 2013, which details all non-farm establishments, including informal, service sector, and publicly-owned firms. We use this data to construct employment per capita and the number of firms per capita at the village level.[2] Second, we obtain information on night-time light for 2010-2013 from the Shrug open data platform (Asher et al., 2019). This is also available at the village level.[3]

We run baseline specification (2), which includes pre-delimitaton×district fixed effects. For night-time the regression includes pre-delimitaton×district×year fixed effects. We present results for the outcomes using two different functional forms: levels and logs (this also deals with outliers). In addition, we show the effect on annual night-time light, excluding villages with zero light (Column 5). We find no significant impact of our variables of interest, except for political competition on the log number of firms.

Table D5: Employment, firms and night-time light

	Employment		Firms		Night-time light		
	Level	Log	Level	Log	Level	Level (no zeros)	Log
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inequality	-.4385	.0041	-.1031	-.0038	-.3018	-.9489	-.0473
	(.4542)	(.0219)	(.1096)	(.0216)	(.6107)	(.8018)	(.0609)
Political competition	-.1240	.0285	-.0263	.0380**	.2127	.5078	.0384
	(.1374)	(.0205)	(.0334)	(.0179)	(.3176)	(.3839)	(.0394)
Inequality ×	-.1845	-.0077	-.0429	.0004	-.0371	-.2634	-.0356
Political competition	(.1710)	(.0121)	(.0413)	(.0099)	(.2118)	(.3617)	(.0290)
Observations	432,182	428,215	432,182	428,215	339,368	181,864	181,864
Mean dependent variable	.132	-3.512	.053	-4.101	4.200	7.837	1.800
Average expenditures	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unit	Village	Village	Village	Village	Village	Village	Village

The independent variables are standardized, and the coefficients thus reflect the impact at average levels. All regressions control for average expenditures, and area characteristics, and pre-delimitation constituency × district fixed effects. The regressions in Columns 5-7 include pre-delimitation constituency × district × year fixed effects. Robust standard errors, clustered at the pre-delimitation constituency × district level, are shown in parentheses. ** significant at 5 percent

[2] To link the villages to constituencies, we employ the matching keys provided in the Shrug database (Asher et al., 2019).

[3] The data is based on the DMSP-OLS annual measures of light luminosity during the night, measured at 1/120 degree.

Appendix E Data Construction

In this section, we outline how we construct our data.

E.1 Census of India 2001

We make extensive use of the 2001 Census of India. We map Census villages as of 2001 into pre- and post-delimitation constituencies based on geocoded maps. In total, there are 483,072 villages in the 2001 Census for the states in our sample. The Census's 2001-2011 concordance table makes it possible to link these villages to the 2011 Census based on state, district and village codes.[4] After doing this exercise, we have a sample of 481,156 Census villages as of 2001.

E.2 Mapping NFHS Households to PCs

We use the GPS coordinates provided by the 2015-2016 National Family and Health Survey (NFHS) to allocate villages to PCs. The GPS coordinates are at the level of survey clusters, which roughly correspond to Gram Panchayats (GPs). To maintain confidentiality, the NFHS randomly displace the GPS coordinates with a maximum of two kilometer for urban clusters and five kilometer for rural clusters. An additional 1% of the rural clusters is displaced with a maximum of ten kilometer.

We derive PCs for each cluster by combining the survey coordinates with the constituency maps. We then merge this with our other data based on state, district, pre- and post-delimitation constituencies. When doing this merge, we lose close to two per cent of the NFHS households. All of these have a combination of district, pre- and post-delimitation constituencies that is not found for any Census village, which indicates either displacement of the survey coordinates or inaccuracies in the constituency map. We drop these observations from our analysis.

[4] The concordance table is available here: http://censusindia.gov.in/pca/cdb˙pca˙census/cd˙block.html. As sub-districts are not consistently coded in the concordance table, we cannot use it in the matching. We drop village codes that have duplicates within state and district. This applies for 0.0005 per cent of the villages only.

E.3 District Level Household and Facility Survey

In this section, we discuss how we merge the District Level Household and Facility Survey (DLHS) with our dataset.

The 2012-2013 DLHS survey provides geocodes for the location of surveyed healthcare facilities, which enables us to map facilities into pre- and post-delimitation constituencies, and link them to the Census village map. We focus on Primary Health Centers (PHCs). Out of the 7,204 surveyed PHCs from the 15 states in our sample, we are able to link 5,704 PHCs with our other data. The remaining PHCs have severe errors in their geocodes, for instance they are located in the wrong states.

We also make use of the 2007-2008 DLHS survey. This survey does not have geocodes, due to which we cannot directly link PHCs to constituencies. Instead, we proceed as follows. We first match villages in the DLHS with the village directory of the 2001 Census. To do this, we follow a procedure similar to Banerjee and Sachdeva (2015) and Calvi and Mantovanelli (2018) and match villages based on state, district, sub-district and population. We drop duplicates in terms of population within sub-districts in both dataset before merging the data. Overall, we are able to unambiguously match about 90% of the DLHS villages (and the same percent of the surveyed rural households) with the Census. Using the Census identifiers we are then able to link the DLHS villages to constituencies. We next link villages to PHCs based on information in the DLHS village questionnaire. Note that a PHC is usually linked to more than one village, and these villages can potentially be located in different constituencies. We proceed as follows. For each PHC, we list all DLHS villages that are linked to it. Among these villages, we then identify the most common pre- and post-delimitation constituency and impute these constituencies to the PHC. For about 90 per cent of the PHCs, all villages belong to the same constituency. In total we are able to successfully match 5,700 out of 7,394 PHCs with our other data using this procedure.

E.4 MGNREGA

Below we describe our procedure to create a GP-level dataset on MGNREGA implementation.

We extract data for the financial years of 2011-2012 to 2013-2014 from the MGNREGA

Public Data Portal. This data includes names of districts, sub-districts and GPs but it has no information on Census identification numbers.

We are able to use the MGNREGA data for all 15 states in our main analysis, except for Rajasthan which has GP names written in Hindi letters. We cannot therefore match this data to the Census. The part of Andhra Pradesh that was carved out to form the new state of Telangana is missing in the MGNREGA dataset as well. As the Census directories for West Bengal and Madhya Pradesh do not contain GP names, we extract those from the Local Government Directory. We then merge these with the Census before merging with the MGNREGA dataset.

We first manually make sure that we correctly match districts and as many sub-districts as possible. We are able to match 4,604 sub-districts out of a total of 4,704 (excluding Rajasthan and the missing districts in Andhra Pradesh). Within each state, district and sub-district we then conduct fuzzy matching based on GP names (after cleaning the location names). We apply the `Masala merge` procedure, developed by Asher and Novosad (2017). The matching procedure is based on the Levenshtein algorithm but is modified to better suit names in Hindi.[5] We are able to match 76.5% of the 2011 Census villages to the MGNREGA dataset (and to the 2001 Census and PCs). This level of matching is comparable to other researchers doing fuzzy matching in the Indian context (Asher and Novosad, 2017; Gulzar and Pasquale, 2017).

[5]The codes for the program can be found here: http://www.dartmouth.edu/ novosad/code.html

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