# The Determinants and Consequences of Political Selection in the Developing World: Evidence from India*

Apurva Bamezai† Siddharth George‡ M. R. Sharan § Borui Sun ¶

Mar 26, 2026

**Abstract**

The competence and representativeness of a political class are widely seen as defining features of democratic quality, yet whether the two can be achieved jointly in developing democracies is an open question. We address this question by linking administrative records on 97 million rural citizens in Bihar, India, to nearly one million candidates contesting village council elections, providing the first large-scale evidence on political entry, selection, and governance. We show that while candidates are drawn from a socioeconomically elite subset of society, they are strongly positively selected on competence (education). Within this pool, however, a sharp trade-off emerges: winners are more competent yet less representative than the candidates they defeat, while candidates for higher-tier offices are more competent yet less representative than those contesting lower tiers. Using close elections, we show that this trade-off has consequences for governance: more competent leaders have better knowledge of governance rules, boast wider bureaucratic networks and implement skill-intensive programs more effectively, but allocate fewer resources to disadvantaged groups and align spending more closely with elite preferences. Finally, we show using a regression discontinuity design (RD) strategy that affirmative action attenuates the trade-off along distinct margins: reservations for marginalized Scheduled Castes (SCs) produce candidates whose socioeconomic profile matches the median SC voter while preserving within-group competence, and gender reservations expand the candidate pool by drawing in women from less elite households. Our findings identify a fundamental tension in political selection in developing democracies, while showing that institutional design can mitigate its costs.

*We thank Martin Mattson, Fred Finan, Saad Gulzar, Guo Xu and Jing Cai for feedback. We thank seminar participants at the Midwest International Economic Development Conference, Indian Statistical Institute (Delhi), NUS Singapore, Georgetown University, Delhi School of Economics and PDRI-DevLab at University of Pennsylvania for some excellent comments.

†Kellogg Institute for International Studies, University of Notre Dame

‡Department of Economics, National University of Singapore

§Department of Agricultural and Resource Economics, University of Maryland

¶Department of Agricultural and Resource Economics, University of Maryland

# 1 Introduction

Leaders play a central role in democracies. Indeed, the view of politicians as "the most important agents of change" (Gulzar, 2021) attains greater salience in the era of strongman leaders the world over. Two attributes of leaders are often emphasized in the literature: competence, defined as the capacity to select and implement policies that achieve their intended goals — an ability typically grounded in human capital, knowledge of administrative rules, and the skill to negotiate with other agents of the state; and representativeness, defined as the capacity to reflect the preferences of a diverse electorate, and typically linked to politicians' identity, class, and occupation.

There is no guarantee, however, that politicians will embody either of these traits, and the two may even be in conflict. Across the world, the median officeholder differs vastly — in identity and preferences — from the median citizen, drawn disproportionately from wealthier, higher-status, and more socially advantaged backgrounds (Gulzar, 2021; Carnes and Lupu, 2023). Beyond this representativeness gap, the channels that bring politicians to office often appear to reward attributes other than merit: dynastic ties, wealth, partisan loyalty, and even criminal records have been shown to predict electoral success in a range of settings (Querubin, 2016; Banerjee and Pande, 2007; **?**). Moreover, even setting aside this selection problem, there is a structural reason to expect competence and representativeness to trade off: the opportunities that produce competence — schooling, exposure to administration, professional networks — are themselves concentrated among elites, so the candidates best equipped to govern are precisely those least able to represent the median voter. This tension is likely to be sharper in developing countries, where inequality is higher, social hierarchies are more entrenched, and political institutions are comparatively nascent (Dal Bó and Finan, 2018). Yet direct evidence on whether and how competence and representativeness co-vary within the same pool of candidates — and on whether they trade off at all — remains scarce.

We document the presence, extent, and consequences of the competence–representativeness tradeoff in local government in Bihar, India. Documenting the tradeoff is typically hard: it requires tracing the full pipeline of political entry — what citizens want in candidates, who among the citizenry contests, and who among the candidates wins — and then asking how leader attributes shape what the state delivers, and how policies that broaden political access reshape each of these margins. Existing work on political selection has examined individual segments of this pipeline, but to our knowledge, no prior paper traces the full pipeline end-to-end, nor studies how inclusion reforms reshape each margin in turn.

Bihar is an excellent setting for studying political selection in low-income democracies. With a population of over 130 million, it accounts for 3.5% of the global population living in a democracy, and it is India's poorest state, with historically weak state capacity. Bihar's local government comprises over 8,000 Gram Panchayats (GPs) – village councils – with a population of over 13,000 that are divided into wards, each with a population of roughly 1,000, with both having directly elected representatives. Three features make the study of Bihar's GP elections especially informative. First, Bihar is highly unequal, so educational and economic opportunities are concentrated among a narrow, unrepresentative elite. Second, it is ethnically diverse and marked by deep caste and religious cleavages, so voters may face a tradeoff between supporting a co-ethnic candidate and the most capable one. Third, local democracy is relatively nascent, and institutions such as political parties that can facilitate positive and inclusive selection are weak or absent in many jurisdictions. Together, these features could bring into sharp focus the tradeoff between competene and representativeness of the political class.

We begin by describing political selection patterns in rural Bihar.[1] To do so, we build, what is to our knowledge, among the largest matches between a political candidate roster and a population census in the literature. We link administrative records on nearly 1 million candidates for local office in Bihar to the Socio-Economic Caste Census (SECC), a household census covering over 97 million rural residents of the state. The matched dataset provides us novel evidence on the education, wealth, occupation, and family background of every candidate — winners and losers alike — and benchmark them against the citizens they were drawn from, their own siblings, and their caste, cohort, and neighbourhood peers.

We measure competence by years of formal education. In our setting, education tracks the skills that matter for local governance: more educated politicians know more about government programmes and have wider professional networks, and an original survey and conjoint experiment with citizens (N = 1,147) show that they rank education among the most important attributes they look for in candidates. We follow others in the literature and measure representativeness by comparing a politician's father's education to the education of other comparable citizens. Father's education has the useful property of being fixed well before the son enters politics, so — unlike wealth or occupation, which a politician son can influence — it provides a clean benchmark of the socioeconomic stratum the politician was born into.

We find that that the candidate pool is more competent and more elite than the citizens they represent. Candidates in open (unreserved) seats for political office have 2.6 more years of schooling (0.67 SD) than the average citizen. Politicians are also 0.49 SD more educated than citizens in their birth cohort, 0.47 SD more educated than citizens in their sub-caste, and 0.34 SD more educated than other men in their household. Politicians are, however, drawn from relatively elite families. Their fathers are 0.28 SD more educated than other comparable citizens (conditional on birth cohort, caste, and neighbourhood) — a gap large enough to confirm that officeholders are drawn disproportionately from the upper end of the socioeconomic distribution.

But elite origin is only part of the story. Holding background fixed, politicians are always more competent than citizens from the same background. This is visible in what

[1]We restrict our focus to rural politicians for two main reasons. First, Bihar remains an overwhelmingly rural state, with only 11% of the population residing in urban areas according to the 2011 Census. Second, the institutional architecture, mandates, and functioning of local bodies differ markedly between rural and urban areas, making it analytically problematic to study them jointly.

we term the *candidate selection frontier*: the relationship between candidates' own education and their fathers' education. It lies above the corresponding curve for citizens – which we call the *citizen mobility curve* – at every point of the distribution, and the gap is substantial. Indeed, this gap survives the strictest comparisons: for instance, a candidate is 0.19 SD more educated than their own non-politician sibling. Political selection in Bihar in open seats is thus meritocratic, but the meritocracy is elite-biased: the pool of competent citizens from which politicians are drawn is itself narrow.

The competence–representativeness tradeoff operates across multiple margins of selection. Candidates for higher-tier GP offices are more competent but less representative than those at the ward level; and, across all tiers, winners are both more competent and more elite than the candidate pool they emerge from. The tradeoff is also sharper along the three dimensions that characterize developing democracies. First, it widens with local inequality: politicians are more educated and less representative in more unequal villages. Second, group size matters. Candidates from larger religious groups are both more competent and less representative, but the two movements are driven by different subgroups: the rise in competence comes from minority Muslim candidates, while the decline in representativeness comes from majority Hindu candidates.[2] Third, political parties discipline selection. Where parties operate, politicians are more competent, yet only noisily more elite — suggesting that party presence expands the competence margin without correspondingly narrowing representation.

Having documented the competence–representativeness tradeoff in selection, we examine its consequences for governance. We collect an original survey of nearly 9,800 citizens across 10 districts eliciting what they want their local government to deliver, and link these responses to administrative records on GP spending plans. Using a close-election regression discontinuity design, we show that GPs governed by more educated leaders allocate less planned expenditure and fewer development projects to the priorities of historically marginalized Scheduled Caste (SC) citizens. The pattern extends to realized service delivery. More educated leaders implement skill-intensive schemes — such as piped water supply and road construction — more effectively, but redistribute less: SC citizens receive fewer NREGS benefits under their tenure. Together, these findings indicate that the tradeoff shapes not only who enters office but also what the state delivers, and to whom.

Given these governance consequences, we next ask whether a common policy to broaden representation — political reservations for disadvantaged groups — alters the competence–representativeness tradeoff. Bihar reserves 17% of GP seats for Scheduled Castes (SCs), in line with their population share. Reservation is assigned through a rule based on the size of the GP SC population, which generates discontinuities we exploit in a regression discontinuity design comparing GPs just above and just below the relevant cutoffs.

[2] This asymmetry is consistent with Banerjee and Pande (2007): when a group is large enough to be nearly assured victory, the marginal return to competence falls; when it is too small to win at all, only the most competent candidates enter.

Reservation lowers the competence of elected politicians but raises their representativeness, exactly in line with the tradeoff observed earlier. The more informative result emerges once we examine selection within the SC group. Because the citizen mobility curves differ sharply between SC and non-SC citizens, comparing all candidates to a pooled citizen benchmark conflates two distinct patterns. When we restrict the comparison to same-group benchmarks, SC candidates are positively selected on competence relative to SC citizens (0.85 SD) by a margin comparable to the non-SC candidate–citizen gap (0.95 SD), but they are far more representative of their own group: the median SC candidate's father has nearly the same education as the median SC. Moreover, SC winners break the broader pattern of the paper: they are both more competent and more representative than the SC candidate pool they are drawn from. Reservation therefore weakens the competence–representativeness trade-off rather than trading one for the other.

We turn next to gender-based reservations: Bihar reserves 45% of GP seats for women under a similar population-threshold rule that permits a parallel RD design to the SC reservation case. As the prior literature would predict, reservation sharply reduces the individual-level competence of elected leaders: women winning in reserved seats have 0.93 SD fewer years of schooling than winners in unreserved seats. Even when each candidate is benchmarked against the distribution of their own gender in the GP, the educational advantage of reserved-seat winners over other women (0.19 SD) is substantially smaller than the advantage of unreserved-seat winners over other men (0.65 SD). More distinctively, reservation meaningfully democratizes the pool of households entering politics: candidate households in reserved seats are less likely to hold salaried government jobs, pay income tax, or sit high on an asset index than those in unreserved seats, though they remain modestly more elite than the average household in the GP. Gender reservation, therefore, broadens representation in two ways: first, by bringing in women into the political fold and second, by bringing in a pool of less elite households.

**Contribution to Literature.** The paper contributes to three strands of literature. Primarily, we add to a growing literature on political selection, first surveyed by Besley (2005) and more recently by Dal Bó and Finan (2018) and Gulzar (2021). The closest precedent is Dal Bó et al. (2017), who, in a seminal contribution, exploit rich Swedish administrative data to compare politicians to the full population and characterize Sweden as an "inclusive meritocracy"—politicians are both more competent than the citizens they represent and drawn from a broad socioeconomic base. We examine these dimensions in a very different setting, the developing-country democracy of Bihar, and document a clear tradeoff: leaders in open seats are highly meritocratic even within their own group, but the candidate pool is drawn from a comparatively elite slice of rural society. Unlike Dal Bó et al. (2017), we go beyond describing patterns of selection – we investigate causal effects along margins central to developing-country democracies. First, we exploit the quasi-random assignment of SC and gender reservations to identify the causal effects of affirmative action on each dimension. Second, we trace the consequences of the competence–representativeness tradeoff for downstream governance.[3]

Within the developing world, evidence on political selection has been thinner and more fragmented. Besley et al. (2012) document selection patterns at the Indian GP level, and Gulzar and Khan (2025) and Gulzar et al. (2021) study, respectively, the supply side of candidacy in Pakistan and information frictions in candidate choice in Nepal. Chaudhuri et al. (2025) use lab-in-the-field data on village-level politicians in West Bengal in India to argue that competence and integrity can pull in different directions — a finding we substantially extend by measuring the competence–representativeness tradeoff at scale across the universe of Bihar GPs and by exploiting the quasi-random assignment of reservations to identify how each dimension responds to the policy lever.[4]

Second, we contribute to the literature on political reservations. Existing work has focused almost exclusively on the downstream effects of reservations — on policy choices, public goods, and beneficiary outcomes (Chattopadhyay and Duflo, 2004; Pande, 2003; Dunning and Nilekani, 2013; Chin and Prakash, 2011; Gulzar et al., 2020). Far less is known about the intermediate step that drives these effects: which members of a reserved group enter office, and how their competence and representativeness compare both to leaders from the same group elected without quotas and to the broader pool of eligible citizens. We provide novel causal evidence on this margin — separately for SC and gender reservations, and along both dimensions of leader quality. Cassan and Vandewalle (2021) show that gender quotas cause a shift in the caste composition of officeholders towards lower castes. We show that quotas additionally democratize the candidate pool even within caste, bringing in less elite households than would otherwise enter politics.

Finally, we contribute to a growing literature in political economy on the functioning of local governments in developing democracies. Existing work has examined the incentives and performance of elected and appointed local leaders (Martinez-Bravo, 2017; Arora et al., 2024), the persistence of non-democratic institutions in shaping subsequent local government outcomes (Martinez-Bravo et al., 2017; Acemoglu et al., 2014), monitoring and accountability in local administration (Olken, 2007; Banerjee et al., 2020), the consequences of polity size (Narasimhan and Weaver, 2024), and the effects of council size and composition (Smith, 2024; Narasimhan and Weaver, 2026). We complement this body of work by shifting attention upstream to who enters local government in the first place. By documenting a tradeoff between competence and representativeness in the candidate pool and tracing its downstream effects on governance, we connect the literature on local government performance to the selection process that determines it.

[3] Subsequent work in rich countries has documented positive selection on competence but weaker social inclusivity (**?**Thompson et al., 2019).

[4] Concurrent ongoing work by Bhusal et al. (2022) examines representativeness in Nepal across a regime transition.

## 2 Background and Context

Bihar is a large, poor, agrarian state in eastern India whose political and economic features make it a natural laboratory for studying political selection in developing democracies. Three features in particular – its scale and representativeness of the developing-world norm, its combination of high inequality and salient group identity, and its decentralized local government with extensive reservations – motivate our focus on this setting. We describe each in turn, along with the institutional details needed to interpret our empirical analysis.

### 2.1 Bihar

**Scale and representativeness.** With a population of over 130 million – roughly 3.5% of the world's population living in a democracy – Bihar is larger than most countries. It is overwhelmingly rural (nearly 90% in 2011) and agrarian, and its democratic institutions, while stable, are younger and less consolidated than those in advanced economies. These features make Bihar broadly representative of the conditions under which most of the world's voters select their leaders, and where we have the least systematic evidence on who enters politics.

**Inequality.** Bihar is a highly unequal agrarian economy. In 2009-10, the land value of a landlord household was 33 times that of an agricultural labour household (**?**). Such inequality concentrates educational and economic opportunities among a narrow elite, creating precisely the conditions under which the competence-representativeness trade-off in political selection is likely to be most acute.

**Caste and group identity.** Caste is central to social and political life. Only 11% of marriages cross caste boundaries (Desai and Vanneman, 2015), and caste hierarchy maps closely onto economic hierarchy: the sub-castes at the bottom of the asset distribution are also those at the bottom of the caste order (Sharan, 2023). Bihar's thousands of sub-castes fall into five broad groupings: the Scheduled Castes (SCs, 17%), historically considered "untouchable"; Scheduled Tribes (STs, 1.7%); Extremely Backward Castes (EBCs, $\sim$35%), carved out of the larger Other Backward Castes (OBCs) grouping; and, at the top, the general castes. The salience of group identity – and the wide variation in group sizes across GPs – provides the variation we exploit to study how demographic composition shapes selection.

### 2.2 Local Governance

Bihar has over 8,000 rural local bodies called Gram Panchayats (GPs), each with a population of roughly 13,000. Each GP is divided into wards of about 1,000 persons. Both units have directly elected heads – GP heads (locally, *Mukhiyas*) and ward members – but GP heads are substantially more powerful, with direct access to state development funds and primary responsibility for implementing welfare schemes. Ward members, by contrast, had no direct access to state funds until 2016 and primarily represent constituents in GP and village meetings (*Gram Sabhas*). Our main analyses focus on GP heads; we use ward members in supplementary validation exercises.

Local elections are conducted every five years by the State Election Commission of Bihar and are hotly contested, with turnout exceeding 60% in 2021 – higher than in recent state or national elections. High turnout, combined with the large stakes of GP head elections, makes this a meaningful setting in which to study political selection.

### 2.3 Political Reservations

A defining feature of Indian local democracy – and a central element of our empirical strategy – is political reservation. Since 2006, Bihar has reserved GP head and ward member seats for historically disadvantaged groups: approximately 45% for women, 17% for SCs, 20% for EBCs, and under 2% for STs. Reservation status is determined by a population-based assignment algorithm (described in detail in Section 7.2), which generates quasi-random variation in the identity of leaders across otherwise similar GPs.

Two features of the reservation regime shape how we interpret our results. First, a constituency's reservation status is fixed for two full election cycles (10 years). For both the 2016 and 2021 elections that we study, reservation status was assigned under the same rule and remained unchanged across the two cycles. This allows us to pool candidates from both elections without conflating selection patterns with changes in the reservation regime, and means that the candidates and voters we observe have had time to adjust to the reservation status of their GP – our estimates reflect steady-state selection rather than transitional dynamics. Second, the overlapping caste and gender components of the algorithm generate independent sources of quasi-random variation, enabling us to separately identify the effects of SC reservation and gender reservation (Section 7.2) on who enters politics.

### 2.4 GP Development Plans

Under the 73$^{rd}$ Constitutional Amendment, local governance in India institutionalises deliberative planning. In Bihar, this is operationalised through the Gram Panchayat Development Plan (GPDP) – an annual document listing all projects the GP intends to undertake, with estimated costs and funding sources, based on consultations at the ward and *Gram Sabha* levels. The GPDP generates detailed administrative data on planned spending by project type, which we combine with a survey of citizen preferences to measure how closely leader choices align with what citizens want (Section 6).

# 3 Data and Measurement

Studying political selection requires three things that are rarely available together: data on candidates *and* non-candidates, a measure of competence, and a way to benchmark representativeness. Our setting offers all three. This section describes the administrative and survey data we assemble, and defends our measurement choices for competence (years of education) and representativeness (father's education).

## 3.1 Data and Matching

We combine two large datasets: the Socioeconomic Caste Census (SECC) of 2011-12 and candidate-level records from the Bihar State Election Commission for the 2016 and 2021 GP head and ward member elections.

**Socioeconomic Caste Census (SECC).** The SECC is a household census covering 97 million individuals across 19 million rural Bihar households. For every citizen, we observe gender, broad caste category, age, occupation, and education, along with household-level information on dwelling characteristics, employment, income sources, asset ownership, and land holdings. Crucially, we also observe who each individual's parents are and who else lives in their household, which allows us to link candidates to their families.

**Candidate data.** The Bihar State Election Commission publishes records of all candidates contesting GP head and ward member elections. Across 2016 and 2021, we observe 909,570 candidate-election records, with data on names, father's or husband's name, age, education, caste category, and votes received.[5]

**Matching.** We match candidates to citizens in the SECC within the same GP using a string-matching algorithm based on name, father's or husband's name, caste category, and gender. We restrict to matches with a similarity score of at least 0.95 to limit false matches; results are robust to alternative thresholds (Figure **??**).

Our overall match rate for our primary population of interest – unreserved GP head candidates – is 60.2%, which compares favourably to other census name-matching work (**??**). Match rates are highest for 2016 male GP head candidates and lowest for 2021 women candidates, reflecting two patterns: the SECC is more outdated relative to the 2021 election, and women's records are harder to match because marriage-related migration moves women across villages and because candidate records do not distinguish father's from husband's name for female candidates. On average, matched candidates are somewhat older than unmatched ones; other differences are modest. Appendix E provides the full breakdown.

[5]These are not unique candidates, since individuals can contest across both elections.

### 3.2 Measuring Competence: Education

Measuring politician competence is inherently challenging, as direct measures of underlying ability are rarely available. We use years of formal education as our primary proxy. Education is standard in this literature – used in studies of politicians in Sweden (Dal Bó et al., 2017), Denmark (Dahlgaard and Pedersen, 2024), and the United States (Thompson et al., 2019) – and has been linked to politicians' policy performance across a range of outcomes, including growth, public goods provision, and inflation control (Besley et al., 2011; Martinez-Bravo, 2017; Göhlmann and Vaubel, 2007; Sørensen, 2023). It is also, practically, the only competence-relevant variable available for the full pool of candidates (Gulzar, 2021). Education has also been criticised as a competence proxy, particularly in unequal societies where it may reflect elite background rather than ability (Carnes and Lupu, 2016; Curto-Grau and Gallego, 2023; Lahoti and Sahoo, 2020; Dal Bó et al., 2017). We take this concern seriously and address it in two ways. First, we compare politicians to their own siblings in Section 4 to isolate within-family variation. Second, we mount three original empirical exercises – a close-election regression discontinuity design (RD) on politician knowledge, a parallel RD on political networks, and a conjoint experiment on voter perceptions – to validate education as a measure of governance-relevant competence in our specific context.

**Knowledge of governance.** In our setting, effective policy implementation depends on politicians' knowledge of rules, procedures, and scheme-specific requirements (Bamezai et al., 2024). We test whether education predicts this knowledge using a close-election regression discontinuity design on ward member races, comparing ward members who narrowly won against less-educated opponents with those who narrowly lost. More educated politicians have substantially greater knowledge of how to implement government schemes across housing, infrastructure, and service delivery (Table A3). This is novel evidence that, in this context at least, education causally affects implementation capacity of leaders. Design details and robustness checks are in Appendix H.

**Political networks.** Effective local governance also requires coordination with higher-level officials and integration into the political system. Using the same close-election RD, we find that more educated politicians are substantially more likely to have the personal contact details of key officials – the Block Development Officer, Block Panchayat Raj officials, and the GP head – and are more likely to be involved in political party activities (Table A4). Education, in other words, travels with the relational capital that local governance demands.

**Voter perceptions.** For education to matter for selection, voters must also treat it as a signal of competence. We draw on an original in-person survey of 1,105 respondents across 48 GPs in Bihar, designed specifically to elicit how citizens evaluate political candidates (Appendix I). When asked what qualities they value in a Panchayat candidate, a majority placed education among the top three, ranking it above household wealth, caste, or prior experience (Figure 5).

A forced-choice conjoint experiment embedded in the same survey confirms this with randomised variation: holding other candidate attributes constant – including caste, family wealth indicators, and political lineage[6] – respondents consistently choose more educated candidates to be more likely to run and win elections. For instance, they perceive a B.A.-holder as 15.5 percentage points more likely to win a Panchayat election than an otherwise-identical 5th-grade pass candidate – a large and precisely estimated effect (Figure 6).

Taken together, education captures both the causal capacity to govern and a voter-salient signal of competence, making it a parsimonious and grounded proxy in our setting.

### 3.3 Measuring Representativeness: Father's Education

Benchmarking whether politicians represent the broader population requires a measure that is not itself a product of political selection. A candidate's own education and wealth are endogenous to their path into politics; we therefore follow Dal Bó et al. (2017) in using *father's* education – specifically, education relative to other males in the same birth cohort – as our primary measure of a candidate's social origins. This allows us to assess whether candidates emerge from households that were historically typical or advantaged in terms of educational access.

Two features of this measure shape our analysis. First, we can match fathers only for male candidates. Women typically leave their natal villages upon marriage, and the candidate records do not consistently identify father's versus husband's name for female candidates. All representativeness analyses using father's education are therefore restricted to male candidates. Second, we match 41.1% of male candidates to their fathers in the 2011 Census village rolls. Matched candidates are slightly more educated (by 0.89 to 1.42 years) and more likely to be non-SC and non-ST than unmatched candidates (Appendix Table A18, Panel B). If anything, this suggests our representativeness sample is modestly tilted toward more elite candidates, which would lead us to *understate* the extent of elite persistence among politicians overall.

The conjoint experiment discussed in Section 3.2 provides complementary evidence that representativeness matters to voters as well as to our analysis: respondents consistently favour candidates from their own caste category (Figure 7). The effects are smaller than for education but robust across subgroups, suggesting that voters in rural Bihar value representativeness as a candidate attribute alongside competence.

[6] The conjoint varied seven attributes independently: education, caste category, gender, behaviour/personality, prior family experience in Panchayat politics, presence of a government worker in the family, and the household's main non-agricultural income source (wage labour, private job, farming, or business). Full design in Appendix I.

# 4 Result #1: Who Becomes A Politician?

Building on the data construction and measurement choices described in the previous section, we now document the baseline patterns of political selection in rural Bihar. Three findings emerge. First, politicians are strongly positively selected on competence: they are substantially more educated than the average citizen, and this gap persists even within narrow comparison groups defined by gender, age cohort, caste, household, and birth family. Second, politicians come from more elite households than the average citizen – their fathers are more educated and wealthier than the typical man of the same generation and caste. Third, and most importantly, these two forces are in tension: the most competent candidates are systematically the least representative, producing a clear competence-representativeness tradeoff that recurs across GPs, offices, and outcomes.

**Estimation Framework** To quantify these selection patterns, we begin with a descriptive comparison of the socioeconomic background of politicians (i.e., candidates in local elections) and other citizens within the same GP. Specifically, we estimate

$$Y_{ig} = \alpha \mathbb{1}\{\text{Candidate}\}_{ig} + \epsilon_{ig}, \tag{1}$$

where $Y_{ig}$ denotes the socioeconomic characteristic of individual $i$ in GP $g$, and $\mathbb{1}\{\text{Candidate}\}_{ig}$ is an indicator equal to one if individual $i$ ran for an unreserved GP head or Ward member seat in the 2016 or 2021 local elections.

To examine politicians' representativeness, we compare the social origins of candidates, measured using their fathers' socioeconomic background, to that of the average citizen within the same GP.

$$Y_{ig} = \beta \mathbb{1}\{\text{Candidate's Father}\}_{ig} + \eta_{ig}, \tag{2}$$

where $\mathbb{1}\{\text{Candidate's Father}\}_{ig}$ is an indicator equal to one if individual $i$ has a child who ran in either the 2016 or 2021 local elections for an unreserved seat.

All dependent variables are standardized within GP so that the coefficients are interpreted relative to the local distribution. The coefficients $\alpha$ and $\beta$ respectively capture the competence and representativeness level of the candidates. $\epsilon_{ig}$ and $\eta_{ig}$ represent the error terms, and standard errors are clustered at the GP level.

Although India has an extensive system of political reservations, we first present descriptive statistics on unreserved seats, which are technically "open" to all citizens of a GP, across genders and castes. This gives us an understanding of what political selection would look like absent reservations. In Section 7.2, we exploit quasi-random variation in reservation status to analyse how reservations impact selection.

### 4.1 Selection on Competence: The Education Gap

**Average patterns.** We find that politicians are significantly more competent than the average citizen. The average citizen in rural Bihar has 3.5 years of schooling. By contrast, politicians in the same GP obtain 2.7 more years of education, an increase of 77% relative to the mean or a 0.67 SD increase (Table 1, column 1). We can also interpret these patterns in the following manner: while the average citizen is merely literate, the average candidate has completed primary schooling. Moreover, while only 6% of citizens in rural Bihar have completed high school, this number is three times as high for politicians at 18.5%.

We find that politicians are more likely to come from highly-educated groups in society. As Table A5 shows, politicians come from age cohorts (column 1) and caste groups (column 2) with higher education than the average citizen. Defining group based on surname, or gender×age cohort × surname cells, we also find that politicians hail from more advantaged social groups. However, the magnitudes already indicate that much of the positive selection is within-group: politicians are 0.67 SD more educated than the average citizen, but come from groups that are on average 0.36 SD more educated. Next, we examine within-group selection more directly.

**Within-group.** What is particularly striking is how positively selected politicians are relative to the average citizen within their social groups. Candidates in elections are 0.56 SD more educated than the average citizen of their gender, 0.49 SD more educated than other citizens in their gender and cohort (e.g. men in their cohort). Furthermore, column 4 shows that candidates are 0.47 SD more educated than citizens in their gender-cohort-caste (i.e. other men of their caste in their cohort). Column 5 shows that politicians are 0.34 SD more educated than other adult members of their household (e.g. other men living in their household). Column 6 is based on a restricted sample where we can identify the father of the citizen. This is a smaller sample since some fathers may have passed away or live in another village. For this restricted sample, we see that politicians are 0.18 SD more educated than their siblings.

**Competence and Electoral Performance.** In Table A6, we see that candidates are more competent in elections for higher-level political positions. Panel A focuses on GP heads, while Panel B focuses on lower-tiered ward members. Column (1) of Panel A shows that GP head candidates are 1.09 SD more educated than the average citizen. This difference falls to 0.59 SD for candidates in ward elections.

Next, comparing across columns, we see that competence is linked to position in the electoral races. While the average politician is 0.67 SD more educated than citizens, winners in GP head elections are a full 1.4 SD (column 2 of Panel A) more educated than the average citizen. This translates to an additional 5.6 years of schooling. Within GP head elections, winners are more educated than runners-up, who are in turn more educated than other candidates (Panel A, columns 2-4). Taken together, these results suggest that voters value education of politicians.

### 4.2 Selection on Representativeness: Elite Persistence

We now turn from competence to the representativeness of candidates. To develop a measure of how elite candidates are, and, conversely, whether their education reflects ability or merely inherited wealth, we compare the characteristics of candidates' fathers to citizens in the same cohort and caste.

Panel B of Table 1 displays results. The average politician's father is 0.24 SD more educated than the average citizen. One possible issue with this is that the educational differential between candidates' fathers and citizens could be mechanically lower because education levels in the past among all men was lower than it is now. To control for this concern, we include cohort fixed effects. We see that politicians' fathers are more educated than their peers: they are 0.28 SD more educated than other men of their caste in their cohort. Thus, politicians do hail not only from more educated and wealthier social groups, but their fathers are also more educated relative to the average man in this social group. In other words, politicians come from advantaged communities and, within these, from advantaged families.[7]

### 4.3 The Competence-Representativeness Tradeoff

The previous two sections establish that politicians in rural Bihar are both positively selected on competence and drawn from more elite households than the average citizen. The central finding of this section is that these two patterns are in tension: gains on one dimension come systematically at the cost of the other. We document this tradeoff through three complementary lenses – the relative magnitudes of the two gaps, the distributional shape of selection, and the direct relationship between competence and representativeness within the pool of politicians themselves.

**The competence gap is substantially larger than the representativeness gap.** The first piece of evidence is simply a comparison of magnitudes. Figure 1 plots the competence and representativeness coefficients side by side across progressively finer comparison groups. In the baseline specification, candidates are 0.67 SD more educated than the average citizen, while their fathers are only 0.24 SD more educated. This 0.43 SD wedge persists as we add controls: within gender and age cohort, the competence gap is 0.49 SD against a representativeness gap of 0.31 SD; within gender, age, and caste, the gap is

[7] While some candidates' fathers live with their sons, 58.65% do not. We could, potentially, assess wealth outcomes for fathers who do not live with sons and compare them with other individuals of their own generation. However, while fathers' current asset wealth could also be influenced by sons' wealth, the same cannot be said for education, since education outcomes are almost always determined before sons are born. Hence the relative difference in fathers' education vis-a-vis sons' education offers the cleanest comparison possible.

0.47 against 0.28. Even in the tightest comparison – politicians' own households – candidates are more educated than their non-politician siblings by 0.34 SD. Candidates are thus substantially more positively selected than their family backgrounds would predict, but their family backgrounds are themselves advantaged.

**Distributional shape of selection.** The kernel density plot in Figures 3 shows. Across both GP head and ward member candidates, the candidate distribution is shifted substantially to the right of the citizen distribution – the competence gap. Candidates' fathers sit somewhat to the right of the citizen distribution as well – the representativeness gap – but the shift is far smaller. Candidates' siblings fall in-between, somewhat closer to the citizen distribution than to the candidate distribution. The picture is one of political selection that pulls substantially on ability within families, but that draws disproportionately from families that are already advantaged.

**The candidate selection frontier and citizen mobility curve.** Figure 4 provides the cleanest visual summary. Panel (a) plots two curves. The *citizen mobility curve* (orange) describes the relationship between father's education and son's education in the underlying GP population – a standard intergenerational mobility curve. The *candidate selection frontier* (green) plots the same relationship among individuals who enter politics. The candidate selection frontier lies clearly above the citizen mobility curve across the entire range of parental backgrounds, confirming that candidates are positively selected at every level of family origin.

Panel (b) positions the average unreserved candidate and winner on this frontier, with the citizen mean shown as a reference point. Two features stand out. First, both the average candidate and the average winner sit far to the right on the x-axis, indicating that politicians are drawn disproportionately from the upper end of the parental education distribution – the "elite origins" finding made visual. Second, winners sit further up and further right than the average candidate: electoral competition selects upward on competence, but it also selects toward more elite origins. The tradeoff is not only a feature of who enters politics; it is reinforced by who wins.

**The tradeoff within the pool of politicians.** Finally, the tradeoff is visible not just between politicians and citizens, but within the pool of politicians itself. Figure 2 disaggregates selection by office, election outcome, and social group. Across all three dimensions, the same pattern recurs: more competent politicians are also less representative. GP heads – the more powerful office – are 1.09 SD more educated than the average citizen, compared to 0.59 SD for ward members; their fathers are 0.53 SD more educated, compared to 0.19 SD for ward members' fathers. Winners are more competent and more elite than runners-up, who are in turn more competent and more elite than other losing candidates. The same pattern holds by caste: upper-caste candidates are both more educated and from more advantaged family backgrounds than SC candidates.

Taken together, these results establish a competence-representativeness tradeoff as a robust feature of political selection in rural Bihar. Politicians are genuinely positively selected on competence – even against their own siblings – but the selection pool tilts toward more elite origins, and electoral competition reinforces rather than offsets this tilt. The next section asks what features of local settings make this tradeoff sharper or more muted.

## 5 Result #2: Determinants of Selection: Inequality, Group Size, and Parties

Following the documentation of a competence-representativeness tradeoff in Section 4, we now examine the factors that drive these selection dynamics. A central question is why this tradeoff is more pronounced in certain settings than others. To investigate this, we leverage the substantial variation in local conditions across GPs in Bihar. We focus on three primary dimensions that may shape the observed selection patterns: (i) local economic and structural characteristics, (ii) demographic group identity and size, and (iii) the institutional presence of political parties. By exploring these factors, we aim to identify the conditions under which the barriers to political entry are most restrictive.

**Estimation Framework.** To examine how selection patterns vary with local features, we augment the baseline specifications in (1) and (2) by interacting the key indicators with a feature, $Feature_g$:

$$Y_{ig} = \alpha_1 \mathbb{1}\{\text{Candidate}\}_{ig} + \alpha_2(\mathbb{1}\{\text{Candidate}\}_{ig} \times Feature_g) + \epsilon_{ig}, \tag{3}$$

$$Y_{ig} = \beta_1 \mathbb{1}\{\text{Candidate's Father}\}_{ig} + \beta_2(\mathbb{1}\{\text{Candidate's Father}\}_{ig} \times Feature_g) + \eta_{ig}. \tag{4}$$

where $Y_{ig}$ denotes the relevant standardized outcome for individual $i$ in GP $g$, and $Feature_g$ denotes one of the GP-level characteristics described below. The coefficients $\alpha_2$ and $\beta_2$ capture how the competence and representativeness gaps vary with the GP-level feature, respectively. Standard errors are clustered at the GP level. We focus on male candidates in caste-unreserved GPs, for two reasons: first, we want to focus on "open" seats where members of all castes can technically contest; second, our representativeness results can only be ascertained for male candidates, since we cannot reliably match female candidates to their fathers.

### 5.1 Inequality

In GPs with high land inequality, candidates are more educated than the average citizen *and* come from more elite families – both gaps widen simultaneously. As shown in column 5 of Table A2, the coefficient on candidates' fathers' education is much higher in high-inequality GPs, consistent with elite capture of political entry in settings where opportunity is concentrated among a narrow class.

By contrast, we find no heterogeneity along two other dimensions one might expect to matter. Political selection does not vary with a GP's poverty status (column 1) or geographic remoteness (column 6). Candidates are positively selected on education across poor and wealthy GPs, remote and central GPs alike.

These findings indicate that the competence-representativeness tradeoff is thus not uniform across Bihar: it is especially stark in setting swhere inequality restricts access to the schooling, wealth, and networks that political entry requires.

### 5.2 Group Diversity and Size

Group identity is central to politics in developing democracies, and Bihar is no exception. Two features of ethnic composition matter: how diverse a GP is overall, and how large a politician's own ethnic group is within the GP. We examine each in turn.

**GP-level diversity.** Columns (2) and (3) of Table A2 report how selection varies with two summary measures of sub-caste composition. Ethnic fractionalization is positively correlated with candidate competence and representativeness, while ethnic polarization is negatively correlated with both. One interpretation, following Banerjee and Pande (2007), is that polarization captures settings with two large competing groups – where sure-win candidates face little selection pressure – while fractionalization captures settings with many small groups, each of which must field quality candidates to compete. The coefficients on both indices are small, however, suggesting that while GP-level diversity co-varies with selection, the relationships are modest in magnitude.

**Own-group size.** A more striking pattern emerges when we examine the size of the politician's *own* ethnic group. Table 2 shows that on average, group size sharpens the tradeoff: competence improves (columns 1 and 2), but representativeness of candidates falls (columns 4 and 5). Crucially, in our strictest common specifications (columns 2 and 5), if group share rises from 0 to 1, competence increases by a smaller amount (0.05 SD) than the fall in representativeness (father's education rises by 0.09 SD).

This, however, masks sharp heterogeneity by group. The representativeness result is driven by the majority (Hindu) group. For Hindu candidates, larger group size leaves competence unchanged but draws candidates from more elite families (father's education rises by 0.07 SD): the tradeoff deepens as the majority group dominates the GP. Minority (Muslim) candidates shape the competence increase with larger group sizes. Larger group size improves Muslim candidate competence (0.13 SD) while leaving representativeness unchanged: the tradeoff eases as the minority group grows.

The most natural explanation once again follows Banerjee and Pande (2007)'s logic. Majority-group politicians are essentially sure winners when their group is very large, reducing the competitive pressure to field capable candidates; elite families instead capture the political pipeline. Minority politicians face almost no chance of winning when their group is too small to clear an electoral threshold; as the group grows, selection pressure rises, and the pool of minority politicians shifts toward more competent candidates. The tradeoff thus depends not just on how diverse a GP is, but on whose perspective one takes – majority politicians face less pressure to be competent in homogeneous settings, while minority politicians benefit from larger group size.

### 5.3 Political Parties

We now turn to showing that parties may somewhat improve the competence-representativeness tradeoff.

Parties are not formally allowed to contest local elections in Bihar, but it is well documented that they play a substantial informal role (Dunning and Nilekani, 2013). We proxy for party presence using the share of ward members in each block who report receiving party support in the baseline survey of over 7,700 ward members conducted by Bamezai et al. (2024). We then estimate the interaction specifications in (3) and (4), replacing $Feature_g$ with this block-level share of party involvement.

Table 3 presents the results. Parties substantially increase candidate competence (columns 1 and 2). The effect on representativeness (column 4) is negative but smaller in magnitude, and – importantly – it is not robust to the inclusion of gender and caste fixed effects. The competence effect, by contrast, is robust across specifications. We therefore interpret the evidence as showing that party presence shifts the pool of candidates toward higher competence without necessarily tilting it toward more elite households.

This result is consistent with the argument that weak party institutions are one reason the competence-representativeness tradeoff is sharper in developing democracies than in advanced ones. Where parties operate – even informally – they appear to ease the tradeoff by actively identifying and supporting more competent candidates, expanding the pool beyond those who would enter politics through family connections or inherited advantage alone.

### 5.4 Taking Stock

Together, these results show that the competence-representativeness tradeoff is not a monolithic feature of political selection in rural Bihar. It intensifies where inequality concentrates opportunity and where majority ethnic groups dominate the electorate. It eases where parties are active and where minority groups grow large enough to compete electorally. The tradeoff, in other words, is shaped by the forces commonly seen in developing democracies – and it is responsive to institutional features. These findings motivate the analysis in Section 7.2, where we examine whether a deliberate policy intervention – political reservation – can reshape the tradeoff further.

# 6 Result #3: Consequences of Political Selection

Having established a systematic tradeoff between competence and representativeness in political selection, we now evaluate whether this tradeoff also appears in governance outcomes. We examine how leader competence—measured by educational attainment—shapes governance along two dimensions. We estimate the causal effect of electing a more competent leader on skill-intensive and representation-intensive governance tasks.

To isolate these effects, we employ a close-election regression discontinuity (RD) design comparing winners who narrowly defeated less educated opponents. We find that electing a high-competence leader improves the implementation of skill-intensive infrastructure projects—such as roads and tap water delivery—but worsens alignment of public spending with disadvantaged citizens' preferences and yields fewer welfare projects and NREGS benefits for Scheduled Caste (SC) households.

## 6.1 Competence and Alignment with Citizen Preferences

Each GP prepares an annual Gram Panchayat Development Plan (GPDP), jointly determined by the village council and citizens. These plans reflect prospective local government spending for the subsequent year. To measure representativeness of plans, we collect data on planned projects and caste-wise (SC/non-SC) citizen preferences for those projects across GPs.

### 6.1.1 Data and Identification Strategy

**GPDP Plan Data:** We scrape all the data from the 2024-25 plan. This covers all GPs and includes, for each planned development project, the estimated cost of the project. This includes roads, drains, piped water, solar street-lights and so on. We identify project-type using descriptions, so as to match each project with citizen preferences.

**Citizen Preferences.** We measure citizen preferences using a phone survey of approximately 10,000 respondents across 10 districts in Bihar.[8] Each respondent was asked to name up to two schemes on which they would like the local government to increase spending. Thus, for every GP and scheme, this allows us to calculate the share of citizens who prefer spending on that scheme.

**Identification Strategy.** We estimate the causal effects of leader competence on development outcomes using a regression discontinuity design (RD) that exploits close GP-level electoral races. Competence is proxied by years of education of the winning leader. The identifying variation comes from elections in which a more educated candidate narrowly defeats a less educated candidate, or vice versa.

[8] These citizens were interviewed as part of the endline survey for (Bamezai et al., 2024).

We combine election data with administrative information on GP Development Plans (GPDPs). Outcomes are measured at the GP $\times$ scheme level and include (i) the number of schemes proposed in GP plans and (ii) planned spending on schemes. These outcomes capture allocation decisions made by GP leadership during the post-election planning period.

Our analysis focuses on GP head elections in 2021 in which the top two candidates differ in whether they have education above the primary level. Specifically, we restrict the sample to GPs where one of the top two candidates (either the winner or the runner-up) has education above primary, while the other has education below primary.

**Running Variable and Treatment.** Let $g$ index GPs. For each GP, the running variable is defined as the vote-share margin between the above-primary and below-primary candidates:

$$MoV_g = VS_g^{above} - VS_g^{below},$$

where $VS_g^{above}$ and $VS_g^{below}$ denote the vote shares of the above-primary and below-primary candidates in GP $g$, respectively. Positive values of $MoV_g$ indicate that the above-primary candidate wins the election.

Treatment is defined as an indicator equal to one if the above-primary candidate wins the election:

$$T_g = \mathbb{1}\{MoV_g > 0\}.$$

In robustness checks, we re-estimate the RD using alternative education cutoffs, including comparisons between candidates with high school/graduate education and those without.

**Empirical Specification.** Let $s$ index schemes, and let $Y_{gs}$ denote the development outcome for scheme $s$ in GP $g$. For each GP-scheme pair, we observe citizen demand for that scheme, measured as the share of citizens in GP $g$ who report preferring scheme $s$, denoted $Pref_{gs}$. We estimate the following local linear RD specification:

$$\begin{aligned} Y_{gs} = \mu_s + \theta_1 Pref_{gs} + \theta_2 T_g + \theta_3 (T_g \times Pref_{gs}) \\ + \gamma_0 f(MoV_g) + \gamma_1 (T_g \times f(MoV_g)) + \varepsilon_{gs}. \end{aligned} \tag{5}$$

where $\mu_s$ are scheme fixed effects and $f(\cdot)$ is a flexible function of the running variable. The function $f(\cdot)$ is allowed to differ on either side of the cutoff at $MoV_g = 0$.

All specifications are estimated using local linear regression discontinuity methods. We use the Calonico–Cattaneo–Titiunik (Calonico et al., 2019) optimal bandwidth selector, and report robust confidence intervals. Standard errors are clustered at the GP level. We show that GPs above and below the threshold are balanced in Table **??**.

### 6.1.2 Results

Table 4 presents results isolating the effects of narrowly electing a more educated GP Head on plan outcomes. In Columns (1) and (2), the coefficients on citizen preferences are large and statistically significant. These estimates indicate that, on average, an increase in citizen support for a public good in GPs quasi-randomly assigned a less competent leader leads to substantial increases in both planned spending (a 10% increase in support is associated with 61% more spending relative to the mean) and project counts. Electing a more educated leader, however, does not lead to systematically better or worse overall alignment between spending and aggregate citizen preferences. The interaction effects are small and statistically indistinguishable from zero.

These overall RD estimates, however, mask a sharp divergence by social group (Columns 3–6): in particular, competence worsens alignment with SC preferences, while improving alignment with non-SC preferences. Column (3) shows that a 10% increase in SC citizens preferring a public good results in an increase in spending of about INR 195,323. However, this responsiveness is reduced by about INR 73,010 in GPs where the leader is more competent, a decline of roughly 37%. Column (4) shows a similar pattern for project counts, with 41% fewer projects aligned with SC preferences in GPs quasi-randomly assigned a more educated leader.

Columns (5) and (6) display the opposite pattern for non-SC citizens: spending increases by 19% along non-SC citizens' preferences in GPs assigned a more educated leader.

Finally, Table A17 shows that patterns are broadly true even we change the definition of more competent to above High School/Graduate: more competent leaders remain considerably better at representing non-SC preferences and worse at representing SC preferences, though some results are no longer statistically significant.

Taken together, these results provide direct evidence of a competence–representativeness trade-off in planning decisions. While citizen preferences strongly shape GP plans overall, electing a more educated leader does not increase aggregate responsiveness to citizen demand. Instead, competence shifts whose preferences are translated into allocations. Under more educated leadership, responsiveness to the preferences of marginalized SC citizens declines, while responsiveness to non-SC preferences increases.

## 6.2 Competence and Policy Implementation Outcomes

Having shown that more competent leaders produce GP development plans that are less aligned with the preferences of marginalized SC citizens, we next examine whether this competence-representativeness trade-off extends to realised implementation. We distinguish between governance tasks that primarily require administrative and technical competence and those that depend more directly on representativeness and distributive responsiveness.

For competence-intensive tasks, we focus on the implementation of infrastructure projects such as piped water schemes, drains, and village roads, which require coordination with line departments, contractor oversight, and bureaucratic engagement. As documented earlier (Table A3), more educated leaders demonstrate greater administrative knowledge and broader professional networks outside their GPs—precisely the capacities we argue constitute competence. *Ex ante*, such advantages should improve performance in infrastructure provision.

For tasks that privilege representativeness, we examine person-days generated under the Mahatma Gandhi National Rural Employment Guarantee Act (NREGA), a pro-poor workfare programme that is particularly salient for marginalized groups. Our preferred measure of representational responsiveness is the number of SC person-days generated under NREGA, which captures the extent to which leaders convert the preferences of marginalized SC citizens into realised programme benefits.

#### 6.2.1 Data and Identification Strategy

**NREGA MIS**: We draw on administrative data from the NREGA Management Information System (MIS), which reports the number of person-days generated at the GP level, both in aggregate and disaggregated by social group. Our primary outcomes are total person-days generated and person-days generated for Scheduled Castes. We restrict attention to person-days generated between 2016 and 2021, corresponding to the tenure of GP heads elected in 2016.

**Mision Antyodaya Data** Our second source of administrative data is the Mission Antyodaya survey, a nationwide village-level assessment conducted by the Government of India to benchmark rural infrastructure and service delivery. The survey covers the near-universe of Bihar's approximately 37,262 revenue villages and provides detailed information on the availability of core public goods.

During our study period, the Government of Bihar prioritised the expansion of basic infrastructure under the Chief Minister's Saat Nischay ("Seven Resolves") programme, including piped tap water (Nal-Jal) and lanes and drains (Nali-Gali) (**?**). Importantly, responsibility for implementing these schemes was devolved to the Panchayati Raj Department, placing elected GP heads at the centre of planning, coordination, and execution. These sectors therefore constitute high-stakes, competence-intensive domains of local governance: successful implementation requires technical oversight, contractor management, and coordination with line departments, rather than merely distributive targeting.

We use Mission Antyodaya data to construct village-level measures of realised infrastructure provision. Specifically, we create: (i) an indicator for the availability of piped tap water, (ii) an index of road availability, and (iii) an index of drainage system availability. Together, these outcomes allow us to test whether leader competence translates into improved performance in infrastructure sectors that demand administrative capacity and bureaucratic engagement.

**Identification Strategy** To estimate the causal effect of leader competence on realised development outcomes, we implement a close-election regression discontinuity (RD) design focusing on GP Head elections held in 2016. As discussed earlier, leader competence is proxied by formal education. Identification comes from GPs in which a more educated candidate narrowly defeats a less educated candidate, or vice versa.

Our analysis is restricted to close elections in which the top two candidates differ along the education margin, with one candidate having education above the primary level and the other having education below the primary level. We define treatment as an indicator for whether the winning GP head has education above the primary school level. The running variable is the margin of victory between the more educated (above primary school) and less educated (primary school or below) candidate.

We estimate local linear RD specifications of the form:

$$Y_g = \mu + \theta T_g + \gamma_1 MoV_g + \gamma_2 (T_g \times MoV_g) + \varepsilon_g, \tag{6}$$

where $Y_g$ denotes the realised development outcome in GP $g$, and $f(\cdot)$ is a linear function of the running variable, allowed to differ on either side of the cutoff at $MoV_g = 0$.

All specifications are estimated using local linear RD methods with Calonico–Cattaneo–Titiunik (Calonico et al., 2019) optimal bandwidth selection and robust bias-corrected confidence intervals. Standard errors are clustered at the GP level.

### 6.2.2 Results

Consistent with earlier results, Table 5 shows that electing a more educated GP Head worsens outcomes for SCs. While overall NREGA work-days do not change significantly (Column (1)), SC work-days decline by roughly 616 days (Column (2)), corresponding to a 15% reduction relative to mean SC employment under NREGA. This pattern is consistent with greater social and economic distance between more competent leaders and the average SC voter, whose preferences place a higher weight on NREGA implementation.

In contrast, more competent leaders perform better on two of the three skill-intensive outcomes we measure: tap water and road indices increase significantly, with effect sizes on the order of one-fifth of a standard deviation (Columns (4) and (5)). We, however, find no effects on drains (Column (6)).

These gains suggest that competence enhances performance in domains where technical capacity and coordination are paramount, even as it weakens responsiveness in policy areas that are most salient to marginalised voters. Together, these findings indicate that competence improves governance where skills matter, but does not uniformly enhance distributive outcomes. Instead, the trade-off between competence and representativeness identified earlier is reflected not only in plans, but also in realised development outcomes.

## 7 Result #4: Policies to Improve Political Selection

In the previous sections, we described the competence-representativeness tradeoff among local politicians in Bihar. Citizens value both attributes, and both attributes affect governance: more competent (and thus less representative) politicians are better at representing elites and undertaking complex development tasks, but are worse at pro-poor programs or representing low-caste preferences.

In open seats, as we have seen, leaders tend to be competent but elite: in other words, the tradeoff skews towards competence and away from representativeness. A natural follow-up question is whether policy interventions that boost representativeness decrease competence, and whether, if they do, the tradeoff is ”worth it”.

We focus on a widely used policy to improve representativeness: affirmative action through political reservations. Affirmative action policies in the form of explicit quotas for disadvantaged groups – called "reservation policies" or simply "reservations" – have been a common tool to increase representativeness among the political class in various countries and are present at various levels in India (Pande, 2003).

Specifically, we causally estimate how reservations for (i) Scheduled Castes (SCs) and (ii) women affect the competence–representativeness trade-off among political leaders. A large literature studies the downstream policy consequences of political reservations (Pande, 2003; Duflo, 2005; Chin and Prakash, 2011), including in Bihar (Dunning and Nilekani, 2013; Kumar and Sharan, 2025). By contrast, far less is known about how reservations shape political entry itself – and, in particular, how they alter the balance between leader competence and representativeness.

Reservations mechanically increase representativeness by expanding political access to historically excluded groups. At the same time, given longstanding disparities in access to education, wealth, and social capital between women(/SCs) and men(/non-SCs), one might *ex ante* expect a decline in average competence among elected leaders under reservation.

Two deeper questions, however, are less straightforward *ex ante*. First, how large is the competence trade-off relative to the gain in representativeness? That is, does reservation substantially erode competence, or does it modestly adjust the composition of leaders while achieving large representational gains? Second – and more importantly from a policy perspective – how do competence and representativeness shift *within* the reserved group? In other words, does reservation primarily enable entry by minorities who are relatively elite within their own group, or does it broaden access to include those who are closer to the average citizen within that group?

This within-group question is critical for understanding the distributional and normative implications of affirmative action. If reservation selects disproportionately from the upper tail of the minority group's education and wealth distribution, it may increase descriptive representation without substantially narrowing social distance between leaders and constituents. By contrast, if it expands entry among less-elite minorities, it may fundamentally alter whose preferences are articulated and acted upon. Empirically addressing this question requires measuring competence and representativeness relative to the full distribution of citizens within each group, an exercise that is typically infeasible. As shown earlier, however, our data allow us to construct precisely such measures.

## 7.1 SC reservation

Since 2006, Bihar reserves slightly over a sixth of the GP head seats in favour of SCs. Each GP is reserved for a period of 10 years. We study the effects on political entry in reserved and unreserved GPs in the 2016 and 2021 elections.

### 7.1.1 Identification Strategy

Our empirical strategy exploits the population-based algorithm used to assign reservations for GP head positions for SCs. This algorithm has been used to estimate the causal effects of reservation in Bihar elsewhere (**?**). In each administrative block – a cluster of roughly 15–16 GPs – the algorithm ranks GPs by their SC population and reserves head positions for those above a block-specific threshold. As a result, GPs just above this threshold are substantially more likely to be reserved for an SC head than those just below it: in practice, crossing the cutoff increases the probability of reservation by about 80 percentage points.

This rule governs reservations in the 2006–2016 cycle. For the subsequent 2016–2026 cycle, the State Election Commission first excludes all GPs that were reserved in the previous cycle and then reapplies the same population-based algorithm to the remaining GPs. Our analysis focuses on GPs lying close to the relevant population thresholds in each cycle. Comparing outcomes for GPs narrowly above and below these cutoffs allows us to causally estimate the effects of SC reservation using a fuzzy regression discontinuity design.[9]

We estimate a fuzzy regression discontinuity design. Formally, for candidate $i$ in GP $g$ and block $b$, with SC population $SCPop_{gb}$, we specify:

$$\begin{aligned} Reserved_{gb} = \gamma_0 + \gamma_1 \mathbb{1}\{SCPop_{gb} \geq T_b\} + \gamma_2(SCPop_{gb} - T_b) \\ + \gamma_3(SCPop_{gb} - T_b)\,\mathbb{1}\{SCPop_{gb} \geq T_b\} + \mu_b + \lambda_t + \eta_{gb}. \end{aligned} \tag{7}$$

$$\begin{aligned} Y_{igb} = \beta_0 + \beta_1 Reserved_{gb} + \beta_2(SCPop_{gb} - T_b) \\ + \beta_3(SCPop_{gb} - T_b)\,\mathbb{1}\{SCPop_{gb} \geq T_b\} + \mu_b + \lambda_t + \epsilon_{igb}. \end{aligned} \tag{8}$$

[9] The reservation rule has been described in more detail in Section F.1.

Here $T_b$ denotes the block-specific SC population cutoff, $lambda_t$ denotes election-year fixed effects, and $\mu_b$ denotes block fixed effects. The unit of observation is the candidate, while the treatment indicator varies at the GP level. Standard errors are clustered at the GP level.

#### 7.1.2 Threats to Validity

**Gender Reservation Imbalance:** Table A10 shows balance across the RD threshold. Most variables are balanced across the threshold. However, one feature of the RD design – discussed in detail in Kumar and Sharan (2025) – is that gender reservation is imbalanced across the RD threshold. This imbalance is a mechanical artefact of the reservation algorithm. Kumar and Sharan (2025) address this issue in two ways: (a) by controlling for whether a seat is gender reserved, and (b) by dropping gender-reserved seats on either side of the threshold.

Our main specification for competence follows approach (b), but we show that our results are robust to using approach (a) too. Option (b) has the additional advantage that it is comparable to our main results, where we focus only on male candidates since we do not observe fathers' education for women candidates, which prevents us from constructing measures of representativeness for women leaders.

#### 7.1.3 Results

**Candidate Selection Frontier** We begin by examining, visually, how reservation affects where the average candidate sits relative to the Citizen Mobility Curve and the Candidate Selection Frontier. Panel (a) of Figure 4 plots both curves: the lower (orange) line traces the relationship between father's education and son's education in the underlying GP population – the Citizen Mobility Curve – while the upper (green) line traces the same relationship among political candidates – the Candidate Selection Frontier. Because political entry involves positive selection, the Candidate Selection Frontier lies above the Citizen Mobility Curve: at any given level of parental background, candidates are more educated than citizens.

Panel (b) indicates where the average candidate and winner is on the frontier. The unreserved candidate is positioned far to the right on the x-axis – coming from a privileged background – and sits high on the y-axis, reflecting strong positive selection into politics. Electoral competition reinforces this: unreserved winners are more competent than the candidates from whom they are drawn, but less representative, consistent with the competence-representativeness trade-off documented earlier.

SC candidates present a strikingly different picture. They come from substantially more representative backgrounds than their unreserved counterparts, lying near the left tail of the father's education distribution. Relative to the Citizen Mobility Curve, SC candidates sit above it, indicating positive selection relative to the GP population. Relative to the

Candidate Selection Frontier, however, they lie below it – suggesting that, at comparable levels of parental background, SC candidates appear somewhat less competent than the typical political entrant.

A natural concern is that this gap reflects differences in underlying mobility regimes rather than weaker selection into politics. If educational mobility is more constrained within SC communities, SC individuals will have lower educational attainment for any given parental background relative to the pooled population. Benchmarking against a frontier estimated over all castes will then understate their competence within their own social group.

Panel (c) addresses this directly by re-estimating both curves after standardising education within caste $\times$ GP, so that all comparisons are made relative to others from the same caste group in the same village. Two findings emerge. First, SC candidates remain more representative than non-SC candidates even within their respective caste groups, confirming that reservation draws candidates from especially representative social backgrounds. Second, once mobility differences are accounted for, SC candidates move above the Candidate Selection Frontier. The apparent competence gap in the pooled comparison therefore largely reflects differences in mobility regimes across caste groups, not weaker selection into politics among SCs.

The pattern for election *winners* differs strikingly across seat types. Among non-SC seats, winners are more competent but less representative than the candidates from whom they emerge – the familiar trade-off. Among SC seats, the pattern reverses: SC winners are simultaneously more representative *and* more competent than the SC candidates from whom they are drawn. Electoral selection within reserved seats thus moves in both directions at once. Reservation therefore substantially increases descriptive representation while still producing leaders who are positively selected relative to the pool of potential entrants.

Having inspected these patterns visually, we now establish them causally via the RD design outlined above.

#### 7.1.4 Regression Discontinuity Design

The regression discontinuity compares GPs that are similar in all respects except that one has reserved status and the other does not. Table A10 in the appendix confirms that GPs on either side of the threshold are balanced on a host of observables, and Panel (a) of Figure A1 confirms that the McCrary test is satisfied.

**Candidates: Compared to all citizens in the GP.** Panel A of Table 6 benchmarks SC candidates in reserved GPs against candidates in unreserved GPs, with all outcomes standardised relative to the distribution of all GP citizens. The average candidate in an unreserved GP is approximately 1 SD more educated than the average citizen. Reservation reduces this premium by 0.62 SD, but the average SC candidate in a reserved GP still remains around 0.38 SD more educated than the average citizen.

Despite this competence advantage, SC candidates come from households that closely resemble the average GP household. Unreserved candidates, by contrast, are substantially more elite: their households score around 0.55 SD higher on a PCA-based wealth index, are 0.20 SD more likely to pay income or professional taxes, and are 0.26 SD more likely to contain a salaried government employee (Columns 2–4). Reservation sharply attenuates all of these gaps. If anything, SC candidates are marginally less wealthy than the average citizen (Column 4).

The clearest evidence on representativeness comes from fathers' education (Column 5). In unreserved GPs, candidates' fathers are on average 0.44 SD more educated than the average citizen. Under reservation, this reverses: fathers of SC candidates are approximately 0.30 SD *less* educated than the average citizen. SC candidates are thus drawn from markedly marginalised household backgrounds, even as they themselves remain more competent than the average GP resident.

**Candidates: Compared to citizens within own caste.** Panel B of Table 6 benchmarks each group of leaders against citizens from their own caste. Along the competence dimension, SC leaders are strongly positively selected: they are on average 0.85 SD more educated than the average SC citizen, compared to 0.95 SD for unreserved leaders relative to non-SC/ST citizens. The selection premium is large in both cases.

Patterns of representativeness are more nuanced. In unreserved GPs, the average candidate household scores approximately 0.50 SD higher on the wealth index than the average non-SC/ST household. This gap narrows by about 0.16 SD under reservation, indicating that reservation attenuates – but does not fully eliminate – selection toward relatively elite households within groups. Because household wealth partly reflects leaders' own competence rather than pre-existing advantage, Column 5 focuses on fathers' education as our preferred representativeness measure. In unreserved GPs, candidates' fathers are 0.38 SD more educated than the average non-SC/ST citizen. Under reservation, this advantage is almost entirely eliminated: fathers of SC candidates closely resemble the average member of their own social group.

Taken together, reserved leaders are strongly selected on competence relative to their own group, while remaining far more representative in terms of household background. Within own-group comparisons, reservation produces candidates who are nearly as competent as unreserved leaders but substantially more representative – helping explain why many studies find little evidence of an equity-efficiency trade-off under caste-based reservation (Pande, 2003; Dunning and Nilekani, 2013).

**Winners: Compared to all citizens in the GP.** Turning from candidates to winners, column (1) of Panel A of Table A8 shows that SC winners are on average 0.88 SD less educated than unreserved winners and come from substantially more marginalised backgrounds (columns (2) - (4)). SC winners are poorer than the average citizen in the GP, unlike their non-SC counterparts who are 0.9 SD higher in wealth score (column 4). Column 5 shows that, on representativeness, SC candidates' fathers are 0.69 SD less educated than the average citizen, compared to +0.64 SD for unreserved winners ($\beta$ = - 1.33 SDs). Nonetheless SC winners are 0.41 SD more educated than the citizens they represent (column 1; non-SC mean is 1.29, $\beta$ = -0.88), indicating that even within reserved seats, electoral competition selects positively on competence.

**Winners: Compared to citizens within own-caste.** Panel B of Table A8 turns to comparisons with own-caste members. Within their own caste group, column 1 shows that SC winners are significantly more educated than the average SC citizen (0.84 SD; non-SC winners are 1.21 SD more educated than non-SC winners; $\beta$ = -0.375), confirming positive selection on competence. Their households are wealthier than the average SC household, but they are less likely to contain a government employee or an income-tax payer – suggesting they come from households that are relatively advantaged in assets but not in the kinds of institutional connections that typically characterise unreserved political elites.

On representativeness, the results are striking. Column 5 shows that SC winners' fathers are 0.36 SD *less* educated than the average SC citizen (non-SC winners' fathers are 0.56 SD more educated than the average non-SC citizen; $\beta$ = -0.92) – meaning they are more representative not only than unreserved winners, but than the average SC candidate. Combined with the competence finding, this confirms the pattern visible in Panel (c) of Figure 4: within reserved seats, electoral selection moves simultaneously toward greater competence *and* greater representativeness relative to the SC candidate pool. The usual trade-off between the two does not apply.

### 7.2 Gender Reservation

Next, we turn to gender-based reservations. We measure competence as before – by years of education. However, unlike in the caste context, we lack direct measures of representativeness for women candidates, since information on fathers' education is unavailable.

We therefore shift focus to household characteristics, asking how the households of women contesting in gender-reserved seats differ from those of candidates contesting in unreserved seats. *Ex ante*, the direction of these differences is ambiguous. If women candidates primarily serve as proxies for male relatives (Amar et al., 2025; Heinze et al., 2025; Mori et al., 2025), gender reservation may leave the pool of contesting households largely unchanged. If not, variation in women's agency across social groups suggests a different possibility: when social or caste norms restrict political participation for women from certain groups, these constraints should shape which households enter politics under gender reservation.[10]

[10]Consistent with this view, Cassan and Vandewalle (2021) show that gender reservation crowds in low-caste households and, in turn, aligns government functioning more closely with low-caste citizen prefer-

### 7.2.1 Identification Strategy

To estimate the effects of gender reservation on political selection, we circumvent the endogeneity of GP reservation status with a fuzzy regression discontinuity (RD) approach. The Bihar government mandates that up to 50% of GP seats must be reserved for women. Within each block, the governments first determines which GPs should have seats reserved for SC, ST, OBC or none. Subsequently, within each grouping, the government reserves up to 50% of seats for women. The details are presented in the Appendix (section F.2), but we offer a stylized explanation below.

For gender reservation within GPs reserved for SC (STs), GPs are arranged in descending order of SC (ST) population and the 50% of GPs are reserved for women. This allows for a clear SC (ST) population threshold, above which GPs are reserved for women. Now, for EBC reserved seats, GPs are arranged in descending order of total population and the top 50% of seats are reserved for women. For caste-unreserved GPs, GPs are arranged in descending order non-SCST population and the top 50% of GPs in the list are reserved for women. Thus, population thresholds exist for each of these groups too.

The running variable is simply the distance of the relevant population to the threshold – which is defined by the mean population of the last GP to be reserved and the first GP that missed out on being reserved. By comparing GPs that narrowly selected for reservation to those that narrowly lost, we are able to capture the causal affects of gender reservation on political selection outcomes using the following two-stage instrumental variables specification:

$$\begin{aligned} Reserved_{gb} &= \gamma_0 + \gamma_1 \mathbb{1}\{FemalePop_{gb} \geq T_b\} + \gamma_2(FemalePop_{gb} - T_b) \\ &\quad + \gamma_3(FemalePop_{gb} - T_b)\,\mathbb{1}\{FemalePop_{gb} \geq T_b\} + X'_{gb} + \mu_b + \lambda_t + \eta_{gb}. \\ Y_{igb} &= \beta_0 + \beta_1 Reserved_{gb} + \beta_2(FemalePop_{gb} - T_b) \\ &\quad + \beta_3(FemalePop_{gb} - T_b)\,\mathbb{1}\{FemalePop_{gb} \geq T_b\} + X'_{gb} + \mu_b + \lambda_t + \epsilon_{igb}. \end{aligned} \tag{9}$$

Here $T_b$ denotes the block-specific Female population cutoff, $lambda_t$ denotes election-year fixed effects, and $\mu_b$ denotes block fixed effects. Considering that the thresholds are determined separately for GPs with different caste reservation status, a vector of controls on GP caste reservation $X'_{gb}$ is also included. The unit of observation is the candidate, while the treatment indicator varies at the GP level. Standard errors are clustered at the GP level.

Following Calonico et al. (2019), we estimate a fuzzy RD with optimal bandwidths. We pool all the running variables together to estimate an "overall" effect of gender reservation. We also report results within separate caste reservation groups.

ences.

**Threats to Validity:** The RD design – like all similar designs – assumes that GPs on either side of the threshold are comparable. Table A12 shows balance. Moreover, Figure A1 shows that McCrary test and assures that there is no manipulation of the running variable around the threshold.

#### 7.2.2 Results

**Impact on Candidate Pool** Table 7 reports the effects of gender reservation on political selection. Panel A compares candidates elected in gender-reserved GPs to candidates elected in unreserved GPs, with all outcomes standardised relative to the distribution of all citizens. Gender reservation is associated with a large decline in the elected candidate's own education: women elected from reserved GPs have, on average, 0.77 SD fewer years of schooling than candidates elected from unreserved GPs. As a result, female leaders are only marginally more educated than the typical citizen in the GP.

Column 2 benchmarks candidates relative to their own gender. The average candidate in unreserved seats is about 0.65 SD more educated than the average male in the GP. The coefficient of -0.458 on female reservation indicates that the average woman candidate is 0.19 SD more educated than the average woman in reserved GPs. Thus, while gender reservation substantially reduces the educational advantage of leaders relative to unreserved candidates and relative to citizens overall, it continues to select women who are meaningfully more educated than other women.

However, focusing solely on the elected woman's own education may overstate the implied loss in effective competence. In our setting, proxy leadership is prevalent and administrative responsibilities are frequently mediated through other household members. If governance capacity is embedded within the household rather than the individual alone, then household-level human capital becomes the more relevant measure of effective competence.

In the Bihar context, Amar et al. (2025) show that the overwhelming majority of proxy governance is done via the husband. Column (3) compares the husband of the woman leader on competence with the governing unreserved leader. The impact of reservation is negative ($\beta$ = -0.15), suggesting that even husbands are less competent than the governing unreserved candidate.

Columns (4) - (6) of Table 7 show that gender reservation brings in less elite and poorer households: gender-reserved candidate households are less likely to have members holding a government job (-0.08 SD), report paying income tax (-0.07 SD) and have lower PCA-based asset index scores (-0.09 SD). They are, however, still more elite than the average household in the GP, since the estimates do not entirely wipe out the substantial advantage unreserved candidate households have.

**Impact on Winners** Panel B of Table 7 shows that the patterns documented for candidates largely persist among elected winners. Under gender reservation, the education of the elected GP head falls sharply: Column 1 shows that years of schooling decline by 0.93 SD relative to unreserved leaders and by 0.65 SD even when we restrict comparisons to members of own gender (Column (2)). However, the effects are smaller when we expand the lens to include the husband of the winner: the husband is about 0.36 SD less educated than the winner in unreserved seats (column 3), indicating that the potential proxy winner is still less competent than the unreserved winner, but remains highly positively selected relative to the underlying population (the unreserved winner is 1.1 SD more educated than the average citizen; thus, the husband is still 0.74 SD more educated than the average citizen). Gender reservation also reduces elite household markers (columns 4- 6) – government employment (-0.22 SD), tax payment (-0.17 SD), and wealth (-0.18 SD) – but households remain somewhat more elite than citizens.

**Gender reservation by caste** Because the gender reservation RD pools across castes, we can examine whether the reduction in competence or the democratisation of the candidate pool is driven by particular caste groups. Table A9 presents these results. The reduction in candidate competence is visible across castes, though it is not statistically significant for SCs — likely reflecting the smaller sample around the SC-gender threshold. The democratisation of household backgrounds, by contrast, is concentrated among SC and unreserved women; the corresponding estimate for OBC women is small and insignificant. No single caste group therefore drives both effects simultaneously, and the overall gender-reservation results reflect broadly overlapping patterns across the three caste-groups.

### 7.3 Discussion: How Reservation Affects the Tradeoff

Caste and gender reservation share a common pattern at the candidate level and diverge at the winner level.

At the candidate level, both forms of reservation move competence and representativeness in the same directions: they broaden the candidate pool toward less elite households and reduce the average competence of entrants. This holds even within-group – SC candidates are less elite relative to their own group than unreserved candidates are relative to theirs, and gender reservation draws in women from less elite households than the households of unreserved candidates. In both cases, representativeness rises and competence falls together.

At the winner level, the two reservations diverge. Across all seat types, winners are more competent than the candidate pools from which they emerge – this holds for unreserved, SC-reserved, and women-reserved seats alike. On representativeness, however, the patterns differ sharply. In unreserved seats, winners come from more elite households than the average unreserved candidate: moving from candidates to winners worsens representativeness even as it improves competence, reinforcing the tradeoff. In SC-reserved seats, the opposite holds: SC winners come from less elite households than the average SC candidate, so winners are both more competent and more representative than the pool they emerge from. Among women-reserved seats, winners appear to come from somewhat wealthier households than the average female candidate, though we cannot fully rule out that this reflects the underlying correlation between competence and household resources.

SC reservation reduces the competence-representativeness tradeoff. Once we account for differences in educational mobility across castes, SC candidates sit above the candidate selection frontier, and SC winners are more competent and more representative than the SC candidate pool. The representativeness gain outweighs the competence loss. For gender reservation, the picture is less clean. Candidate competence falls, including within own-group comparisons, and we cannot sign the net welfare effect. What we can document is that the representativeness gain from gender reservation operates along two distinct margins: at the individual level (women replace men), and at the household level (entering candidates come from less elite backgrounds). Our data allow us to measure both margins at scale, even where their net welfare implications remain difficult to assess.

## 8 Conclusion

This paper has documented a tradeoff between competence and representativeness in political selection in a developing democracy. Linking administrative records on 97 million rural residents of Bihar to nearly one million candidates contesting village council elections, we show that this tradeoff appears at every stage of the selection pipeline: politicians are drawn from a relatively elite slice of rural society even as they are positively selected on competence within it, and the candidate selection frontier we estimate lies above the citizen mobility curve at every point in the distribution. The tradeoff sharpens at the winning margin and steepens further across tiers of local government. It also has consequences for governance: using a close-election regression discontinuity design, we find that more educated winners deliver skill-intensive public goods more effectively but redistribute less to Scheduled Caste citizens and tilt local spending toward elite preferences.

The findings in this paper potentially explain some of the findings in the literature on political reservations. For caste-based reservations, a growing body of work (Bardhan et al., 2010b,a; Gulzar et al., 2020; Kumar and Sharan, 2025) finds little or no equity-efficiency tradeoff: aggregate public good provision is largely unchanged under reserved leadership while the share flowing to the targeted group rises. Our selection facts rationalize this pattern. If the equity content of governance is shaped by the representativeness of officeholders and its efficiency by their competence, then a reservation regime that brings in winners who are representative of the median disadvantaged groups voter, yet highly competent — as we find for SC reservations — should produce exactly that pattern. The picture for gender reservations is more complex. Early work pointed to clear gains (Chattopadhyay and Duflo, 2004; Beaman et al., 2012; Iyer et al., 2012), but more recent work has produced more mixed results, with smaller, heterogeneous, or null effects on broader policy outcomes and, in some cases, backlash on the very margins reservations were designed to improve (Bagues and Campa, 2021; Brulé, 2020; Karekurve-Ramachandra and Lee, 2020; Hessami and Lopes da Fonseca, 2020).[11] Our selection-side evidence offers a way to make sense of this more recent body of results. The within-group competence loss we measure under gender reservation is large enough that both the individual and household-level representation gains we identify may not, in every setting, be enough to offset it. Whether women's reservations deliver pro-poor outcomes through this household-democratization channel is, in our view, the most natural direction for future work.

[11] The literature on gender quotas outside India is similarly heterogeneous. Effects are concentrated on women's rights, public health, and child-related spending; broader outcomes are more sensitive to institutional context, party gatekeeping, and quota design (Clayton, 2021; Hessami and Lopes da Fonseca, 2020).

## References


Acemoglu, D., T. Reed, and J. A. Robinson (2014): "Chiefs: Economic Development and Elite Control of Civil Society in Sierra Leone," *Journal of Political Economy*, 122, 319–368.

Amar, P., A. Bamezai, and R. Kumar (2025): "Mere Proxies or Genuine Leaders? Women in Local Politics in the Context of Gender Quotas," SSRN Working Paper No. 5200785.

Arora, A., S. George, N. Mantha, V. Rao, and M. R. Sharan (2024): "(When) Do Politicians Govern Better than Bureaucrats?" *Working Paper*.

Bagues, M. and P. Campa (2021): "Can Gender Quotas in Candidate Lists Empower Women? Evidence from a Regression Discontinuity Design," *Journal of Public Economics*, 194, 104315.

Bamezai, A., S. George, S. Hari, and M. R. Sharan (2024): "Learning to Govern: The Impact of Politicians' Peer Networks," Stage-1 (Pre-Results) Acceptance, Journal of Development Economics. SSRN Working Paper No. 4664964.

Banerjee, A., E. Duflo, C. Imbert, S. Mathew, and R. Pande (2020): "E-Governance, Accountability, and Leakage in Public Programs: Experimental Evidence from a Financial Management Reform in India," *American Economic Journal: Applied Economics*, 12, 39–72.

Banerjee, A. V. and R. Pande (2007): "Parochial politics: Ethnic preferences and politician corruption," .

Bardhan, P., D. Mookherjee, and M. Parra Torrado (2010a): "Impact of Political Reservations in West Bengal Local Governments on Anti-Poverty Targeting," *Journal of Globalization and Development*, 1.

Bardhan, P. K., D. Mookherjee, and M. P. Torrado (2010b): "Impact of Minority Reservations on Targeting in West Bengal Local Governments," *Some Contemporary Issues in Development and Growth Economics*.

Beaman, L., E. Duflo, R. Pande, and P. Topalova (2012): "Female Leadership Raises Aspirations and Educational Attainment for Girls: A Policy Experiment in India," *Science*, 335, 582–586.

Besley, T. (2005): "Political Selection," *Journal of Economic Perspectives*, 19, 43–60.

Besley, T., J. G. Montalvo, and M. Reynal-Querol (2011): "Do Educated Leaders Matter?" *The Economic Journal*, 121, F205–F227.

Besley, T., R. Pande, and V. Rao (2012): "Just rewards? Local politics and public resource allocation in South India," *The World Bank Economic Review*, 26, 191–216.

Bhusal, B., M. Callen, S. Gulzar, R. Pande, S. A. Prillaman, and D. Singhania (2022): "Does Revolution Work? Evidence from the Birth of Nepal's Federal Democracy," Working Paper.

Brulé, R. E. (2020): "Reform, representation, and resistance: The politics of property rights' enforcement," *The Journal of Politics*, 82, 1390–1405.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik (2019): "Regression discontinuity designs using covariates," *Review of Economics and Statistics*, 101, 442–451.

Carnes, N. and N. Lupu (2016): "What Good Is a College Degree? Education and Leader Quality Reconsidered," *The Journal of Politics*, 78, 35–49.

——— (2023): "The economic backgrounds of politicians," *Annual Review of Political Science*, 26, 253–270.

Cassan, G. and L. Vandewalle (2021): "Identities and public policies: Unexpected effects of political reservations for women in india," *World Development*, 143, 105408.

Chattopadhyay, R. and E. Duflo (2004): "Women as policy makers: Evidence from a randomized policy experiment in India," *Econometrica*, 72, 1409–1443.

Chaudhuri, A., V. Iversen, F. R. Jensenius, and P. Maitra (2025): "Selecting the 'Best'? Competing Dimensions of Politician Quality in the Developing World," *British Journal of Political Science*, 55, e81.

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

Clayton, A. (2021): "How Do Electoral Gender Quotas Affect Policy?" *Annual Review of Political Science*, 24, 235–252.

Curto-Grau, M. and A. Gallego (2023): "How Do the Educated Govern? Evidence from Spanish Municipalities," in *Unequal Democracies: Public Policy, Responsiveness, and Redistribution in an Era of Rising Economic Inequality*, ed. by N. Lupu and J. Pontusson, Cambridge University Press.

Dahlgaard, J. O. and R. T. Pedersen (2024): "Inclusive Meritocracy: Ability and Descriptive Representation Among Danish Politicians," *Political Science Research and Methods*, 1–24, forthcoming/Online first.

Dal Bó, E. and F. Finan (2018): "Progress and Perspectives in the Study of Political Selection," *Annual Review of Economics*, 10, 541–575.

Dal Bó, E., F. Finan, O. Folke, T. Persson, and J. Rickne (2017): "Who Becomes a Politician?" *The Quarterly Journal of Economics*, 132, 1877–1914.

Desai, S. and R. Vanneman (2015): "India human development survey-ii (ihds-ii), 2011-12. icpsr36151-v2," *Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]*, 31.

Duflo, E. (2005): "Why political reservations?" *Journal of the European Economic Association*, 3, 668–678.

Dunning, T. and J. Nilekani (2013): "Ethnic quotas and political mobilization: caste, parties, and distribution in Indian village councils," *American political Science review*, 107, 35–56.

Göhlmann, S. and R. Vaubel (2007): "The Educational and Occupational Background of Central Bankers and Its Effect on Inflation: An Empirical Analysis," *European Economic Review*, 51, 925–941.

Gulzar, S. (2021): "Who Enters Politics and Why?" *Annual Review of Political Science*, 24, 253–275.

Gulzar, S., N. Haas, and B. Pasquale (2020): "Does Political Affirmative Action Work, and for Whom? Theory and Evidence on India's Scheduled Areas," *American Political Science Review*, 114, 1230–1246.

Gulzar, S., Z. Hai, and B. K. Paudel (2021): "Information, candidate selection, and the quality of representation: Evidence from Nepal," *The Journal of Politics*, 83, 1511–1528.

Gulzar, S. and M. Y. Khan (2025): "Good politicians: Experimental evidence on motivations for political candidacy and government performance," *Review of Economic Studies*, 92, 339–364.

Heinze, A. R., R. E. Brulé, and S. Chauchard (2025): "Who Actually Governs? Gender Inequality and Political Representation in Rural India," *The Journal of Politics*, 87.

Hessami, Z. and M. Lopes da Fonseca (2020): "Female Political Representation and Substantive Effects on Policies: A Literature Review," *European Journal of Political Economy*, 63, 101896.

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

Karekurve-Ramachandra, V. and A. Lee (2020): "Do Gender Quotas Hurt Less Privileged Groups? Evidence from India," *American Journal of Political Science*, 64, 757–772.

Kumar, C. and M. R. Sharan (2025): "The Short- and Long-Run Distributional Consequences of Political Reservations," R&R, Journal of the European Economic Association.

Lahoti, R. and S. Sahoo (2020): "Are Educated Leaders Good for Education? Evidence from India," *Journal of Economic Behavior & Organization*, 176, 42–62.

Martinez-Bravo, M. (2017): "The Local Political Economy Effects of School Construction in Indonesia," *American Economic Journal: Applied Economics*, 9, 256–289.

Martinez-Bravo, M., P. Mukherjee, and A. Stegmann (2017): "The Non-Democratic Roots of Elite Capture: Evidence From Soeharto Mayors in Indonesia," *Econometrica*, 85, 1991–2010.

Mori, Y., R. Manjula, D. Rajasekhar, T. Kurosaki, and J. Goto (2025): "Who Becomes a Politician in a Gender Quota System? Evidence from India," *World Development*, 188, article 106898.

Narasimhan, V. and J. Weaver (2024): "Polity Size and Local Government Performance: Evidence from India," *American Economic Review*, 114, 3385–3426.

——— (2026): "The Limits of Political Representation: Evidence from India," *American Economic Review: Insights*, conditionally Accepted.

Olken, B. A. (2007): "Monitoring Corruption: Evidence from a Field Experiment in Indonesia," *Journal of Political Economy*, 115, 200–249.

Pande, R. (2003): "Can mandated political representation increase policy influence for disadvantaged minorities? Theory and evidence from India," *American Economic Review*, 93, 1132–1151.

Querubin, P. (2016): "Family and politics: Dynastic persistence in the Philippines," *Quarterly Journal of Political Science*, 11, 151–181.

Sharan, M. R. (2023): "Making the Bihar Caste Census Better," *The India Forum*.

Smith, C. (2024): "Is Basic Democracy Enough?" *Working Paper*, reject and Resubmit, Quarterly Journal of Economics.

Sørensen, R. J. (2023): "Educated Politicians and Government Efficiency: Evidence from Norwegian Local Government," *Journal of Economic Behavior & Organization*, 210, 163–179.

Thompson, D. M., J. J. Feigenbaum, A. B. Hall, and J. Yoder (2019): "Who Becomes a Member of Congress? Evidence from De-Anonymized Census Data," NBER Working Paper 26156, National Bureau of Economic Research.

# 9 Tables

Table 1: Political Selection Among Candidates Contesting for Unreserved Seats

| | Years of Schooling | | | | | |
|---|---|---|---|---|---|---|
| | Baseline<br>(1) | Gender<br>(2) | Gender +<br>Age Cohort<br>(3) | Gender +<br>Age + Caste<br>(4) | Gender +<br>Household<br>(5) | Father<br>(6) |
| *Panel A - Competence: Comparison between Citizens and Candidates* | | | | | | |
| Candidate | 0.673*** | 0.561*** | 0.492*** | 0.474*** | 0.344*** | 0.185*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) | (0.007) |
| *Panel B - Representativeness: Comparison between Citizens and Candidates Fathers* | | | | | | |
| Candidate's Father | 0.242*** | 0.106*** | 0.306*** | 0.282*** | 0.158*** | |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | |
| Observations | 97,349,644 | 97,349,644 | 97,348,519 | 97,348,519 | 96,385,396 | 10,856,994 |

This table reports regression estimates of differences in years of education between individuals who have ever run for Mukhiya or Ward office in unreserved seats and those who have never run for office, using data from the 2016 and 2021 Panchayat elections. Panel A reports differences between candidates and citizens, while Panel B reports differences between candidates' fathers and citizens. The dependent variable, years of schooling, is standardized within GP. Columns (2)–(6) sequentially include fixed effects for gender (2); gender and age cohort (3); gender, age cohort, and caste (4); gender and household (5); and father (6). Standard errors are clustered at GP-level and reported in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table 2: Heterogeneous Selection by Ethic Group Size

| | Competence | | | Representativeness | |
|---|---|---|---|---|---|
| | Baseline | Gender + Age + Caste | Father | Baseline | Gender + Age + Caste |
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: All Population* | | | | | |
| Candidate | 0.620*** | 0.424*** | 0.171*** | | |
| | (0.020) | (0.019) | (0.031) | | |
| Candidates X Group Share | 0.056** | 0.046** | 0.016 | | |
| | (0.022) | (0.022) | (0.035) | | |
| Candidate Father | | | | 0.123*** | 0.194*** |
| | | | | (0.018) | (0.018) |
| Candidates Father X Group Share | | | | 0.133*** | 0.092*** |
| | | | | (0.021) | (0.021) |
| Observations | 94,770,823 | 94,769,723 | 10,677,589 | 94,770,823 | 94,769,723 |
| *Panel B: Hindu Population* | | | | | |
| Candidate | 0.676*** | 0.420*** | 0.254*** | | |
| | (0.033) | (0.032) | (0.052) | | |
| Candidates X Group Share | -0.004 | 0.033 | -0.074 | | |
| | (0.037) | (0.035) | (0.058) | | |
| Candidate Father | | | | 0.077** | 0.067** |
| | | | | (0.032) | (0.032) |
| Candidates Father X Group Share | | | | 0.186*** | 0.226*** |
| | | | | (0.036) | (0.035) |
| Observations | 79,978,946 | 79,978,012 | 9,155,314 | 79,978,946 | 79,978,012 |
| *Panel C: Muslim Population* | | | | | |
| Candidate | 0.499*** | 0.382*** | 0.119*** | | |
| | (0.024) | (0.024) | (0.035) | | |
| Candidates X Group Share | 0.128** | 0.128** | 0.043 | | |
| | (0.053) | (0.053) | (0.077) | | |
| Candidate Father | | | | 0.124*** | 0.220*** |
| | | | | (0.023) | (0.023) |
| Candidates Father X Group Share | | | | 0.004 | 0.006 |
| | | | | (0.049) | (0.049) |
| Observations | 14,791,877 | 14,791,711 | 1,517,817 | 14,791,877 | 14,791,711 |

This table reports heterogeneity in political selection by ethnic group size, using data from the 2016 and 2021 Gram Panchayat elections. Panel A pools all population and interacts an indicator for ever standing for office with the own-group population share at the GP level. Panels B and C restrict the sample to Hindu and Muslim individuals, respectively, and estimate the analogous specification using each group's own population share. Columns (1)–(3) report differences between candidates and citizens; columns (4)–(5) report differences between candidates' fathers and citizens. Columns (2) and (5) include gender, age-cohort, and caste fixed effects, and column (3) additionally includes father fixed effects. All dependent variables are standardized within GP. Standard errors, clustered at the GP level, are reported in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Heterogeneous Selection by Party Affiliation

| | Competence | | | Representativeness | |
|---|---|---|---|---|---|
| | Baseline | Gender + Age + Caste | Father | Baseline | Gender + Age + Caste |
| | (1) | (2) | (3) | (4) | (5) |
| Candidate | 0.574*** | 0.394*** | 0.144*** | | |
| | (0.026) | (0.025) | (0.031) | | |
| Candidates X Party Involv. | 0.463*** | 0.402*** | 0.168 | | |
| | (0.118) | (0.113) | (0.138) | | |
| Candidate Father | | | | 0.197*** | 0.250*** |
| | | | | (0.025) | (0.024) |
| Candidates Father X Party Involv. | | | | 0.189* | 0.132 |
| | | | | (0.111) | (0.111) |
| Observations | 26,083,033 | 26,082,888 | 2,939,161 | 26,083,033 | 26,082,888 |

This table reports heterogeneity in political selection by party involvement, using data from the 2016 and 2021 Gram Panchayat elections. We examine heterogeneity by interacting an indicator for ever standing for office with the share of candidates in the block supported by any political party. Columns (1)–(3) report differences between candidates and citizens; columns (4)–(5) report differences between candidates' fathers and citizens. Columns (2) and (5) include gender, age-cohort, and caste fixed effects, and column (3) additionally includes father fixed effects. All dependent variables are standardized within GP. Standard errors, clustered at the GP level, are reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table 4: Alignment of Public Spending with Citizen Preferences

| | Overall | | SC Pref. | | Non-SC Pref. | |
|---|---|---|---|---|---|---|
| | Spending | Projects | Spending | Projects | Spending | Projects |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Above Primary | -4136.251 | -0.127 | -33495.772 | -0.061 | -1121.092 | -0.140 |
| | (40561.287) | (0.127) | (64144.157) | (0.216) | (41303.792) | (0.130) |
| Pref. | 2790806.395*** | 7.246*** | 1953232.499*** | 5.684*** | 2423916.218*** | 6.229*** |
| | (208218.051) | (0.515) | (242999.214) | (0.685) | (192146.563) | (0.484) |
| Above Primary × Pref. | 160525.064 | 0.170 | -730101.491** | -2.337*** | 452260.136* | 0.916 |
| | (277697.717) | (0.720) | (315195.252) | (0.861) | (258905.339) | (0.680) |
| Dep. Mean | 451465.14 | 1.29 | 471101.52 | 1.34 | 449939.43 | 1.29 |
| Bandwidth | 0.12 | 0.17 | 0.12 | 0.17 | 0.12 | 0.17 |
| Observations | 5,145 | 6,735 | 2,430 | 3,045 | 5,025 | 6,585 |

This table reports the heterogeneous effects of electing a more educated Mukhiya—defined as having above-primary education—on government scheme outcomes by local citizen preferences. Estimates are obtained from a close-election regression discontinuity design. Citizen preferences are measured across a comprehensive set of local public goods and welfare schemes, including water and sanitation, infrastructure, and social protection. We control for scheme-specific measures of citizen preferences and include interactions between these measures and the treatment indicator. The outcome variables are scheme-level expenditures (*Spending*) and the number of projects implemented (*Projects*). Columns (1)–(2) use preferences of the overall population, Columns (3)–(4) use preferences of the Scheduled Caste population, and Columns (5)–(6) use preferences of the non–Scheduled Caste population. All specifications include scheme fixed effects. Standard errors are clustered at the running-variable level and reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table 5: Effects of Leader Competence on Local Governance Outcomes

| | Distributive | | | Skill-intensive | | |
|---|---|---|---|---|---|---|
| | NREGA Work-Days | SC Work-Days | SC (%) Work-Days | Tap Water | Road Index | Drainage Index |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Above Primary | -1193.774 | -616.843$^{*}$ | -0.022 | 0.160$^{*}$ | 0.174$^{*}$ | -0.009 |
| | (1266.620) | (326.622) | (0.015) | (0.092) | (0.099) | (0.097) |
| Dep. Mean | 15841.96 | 2457.75 | 0.17 | 0.00 | 0.02 | -0.02 |
| Bandwidth | 0.15 | 0.13 | 0.13 | 0.17 | 0.12 | 0.13 |
| Observations | 1,726 | 1,553 | 1,554 | 1,799 | 1,422 | 1,482 |

This table reports the effects of electing a more educated Mukhiya—defined as having above-primary education—on government scheme outcomes. Estimates are obtained from a close-election regression discontinuity design using the 2016 Panchayat elections. The treatment variable (*Above Primary*) is a binary indicator equal to one if the winning candidate has above-primary education in the Mukhiya election. Columns (1)–(3) report effects on NREGA distributive outcomes: average annual total workdays generated (1), average annual workdays generated for Scheduled Castes (2), and the share of workdays generated for Scheduled Castes (3). Columns (4)–(6) report effects on skill-intensive infrastructure outcomes, including an indicator for the availability of piped tap water (4), an index of road availability (5), and an index of drainage system availability (6). The sample is restricted to Gram Panchayats in which the top two candidates' education levels straddle the above-primary threshold, with one candidate above and one below primary education. Standard errors are clustered at the running-variable level and reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table 6: Effects of SC Reservation on Selection for Mukhiya Candidates

| | Yrs of Schooling | Representativeness | | | |
|---|---|---|---|---|---|
| | Candidate Edu Yrs | Gov. Job | Income Tax | Wealth Score | Father Edu Yrs |
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: Comparison to all citizen* | | | | | |
| SC RSVN | -0.626$^{***}$ | -0.283$^{***}$ | -0.321$^{***}$ | -0.639$^{***}$ | -0.744$^{***}$ |
| | (0.051) | (0.051) | (0.049) | (0.044) | (0.051) |
| Dep. Mean | 1.01 | 0.26 | 0.20 | 0.55 | 0.44 |
| Bandwidth | 141.557 | 150.272 | 143.460 | 141.613 | 159.372 |
| Observations | 10,768 | 11,430 | 10,863 | 10,761 | 6,381 |
| *Panel B: Comparison to citizen of own group* | | | | | |
| SC RSVN | -0.105$^{**}$ | -0.152$^{***}$ | -0.174$^{***}$ | -0.161$^{***}$ | -0.358$^{***}$ |
| | (0.052) | (0.051) | (0.039) | (0.044) | (0.053) |
| Dep. Mean | 0.95 | 0.25 | 0.18 | 0.50 | 0.38 |
| Bandwidth | 140.548 | 150.184 | 351.059 | 148.457 | 160.452 |
| Observations | 10,742 | 11,318 | 19,910 | 11,293 | 6,412 |

This table reports the effects of Scheduled Caste (SC) reservation on political selection outcomes for Mukhiya candidates in the 2016 and 2021 Panchayat elections. Estimates are obtained from a regression discontinuity design around the population threshold for SC reservation. Columns (1)–(5) report results for the following candidate-level outcomes: standardized years of education (1); an indicator for whether any household member holds a salaried government job (2); an indicator for whether any household member pays income or professional taxes (3); a PCA-based wealth index constructed using land ownership, housing characteristics, and asset ownership (4); and the candidate's father's years of education (5). Panel A reports outcomes standardized relative to all citizens within the GP, while Panel B reports outcomes standardized relative to individuals from the same caste within the GP. The sample is restricted to seats unreserved for women. All specifications include block fixed effects and election-year controls. Standard errors are clustered at the GP level and reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

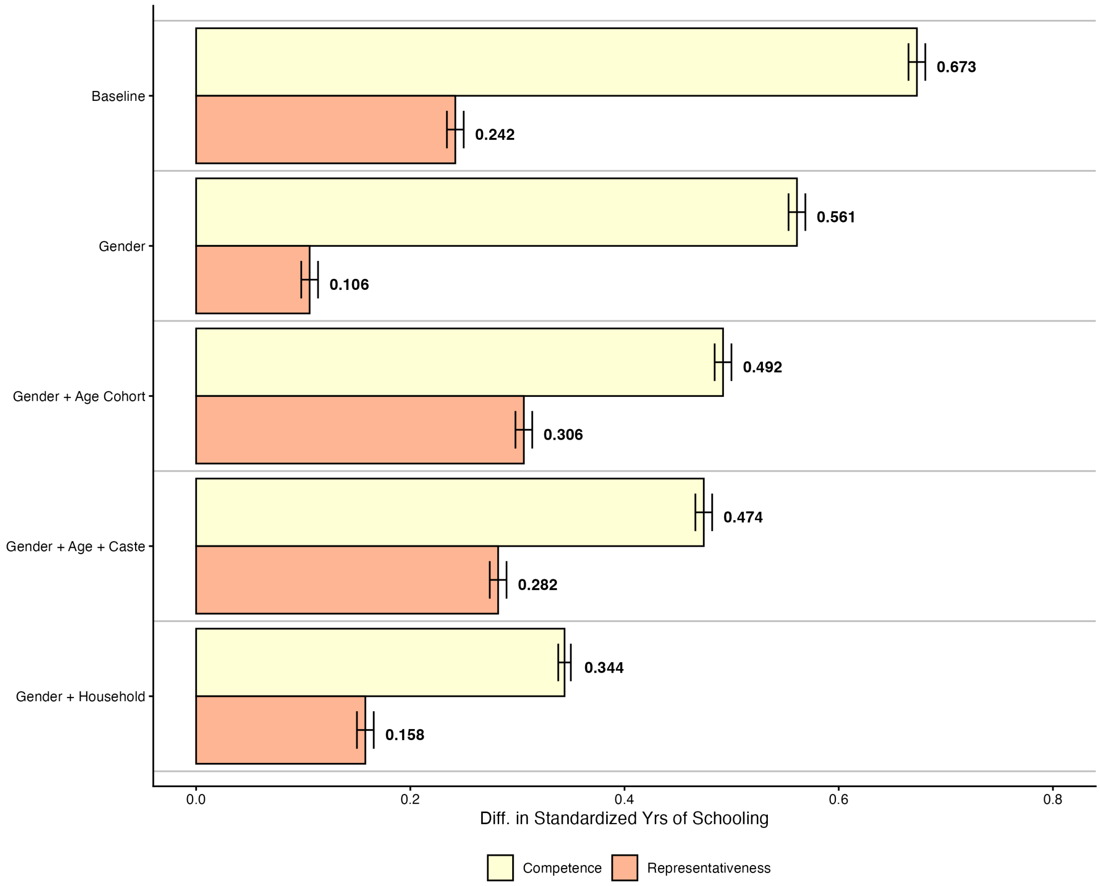
Table 7: Effects of Female Reservation on Political Selection for Mukhiya Candidates

| | Yrs of Schooling | | | Representativeness | | |
|---|---|---|---|---|---|---|
| | Edu Yrs (All Citizen) (1) | Edu Yrs (Own Group) (2) | Husband Edu Yrs (3) | Gov. Job (4) | Income Tax (5) | Wealth Score (6) |
| | | | *Panel A: Candidates* | | | |
| Female RSVN | -0.765*** | -0.458*** | -0.147*** | -0.081*** | -0.074*** | -0.091*** |
| | (0.024) | (0.024) | (0.031) | (0.026) | (0.024) | (0.022) |
| Dep. Mean | 0.80 | 0.65 | 0.80 | 0.21 | 0.14 | 0.32 |
| Bandwidth | 858.596 | 855.351 | 873.669 | 799.300 | 873.669 | 977.299 |
| Observations | 44,583 | 44,552 | 36,498 | 43,369 | 44,737 | 46,487 |
| | | | *Panel B: Winners* | | | |
| Female RSVN | -0.921*** | -0.619*** | -0.364*** | -0.216** | -0.176* | -0.190*** |
| | (0.073) | (0.074) | (0.089) | (0.086) | (0.093) | (0.070) |
| Dep. Mean | 1.11 | 0.95 | 1.11 | 0.32 | 0.30 | 0.65 |
| Bandwidth | 489.012 | 473.452 | 691.411 | 566.563 | 539.418 | 642.694 |
| Observations | 3,294 | 3,249 | 3,058 | 3,528 | 3,456 | 3,759 |

This table reports the effects of female reservation on political selection outcomes for Mukhiya candidates and winners in the 2016 and 2021 Panchayat elections. Estimates are obtained from a regression discontinuity design exploiting the population threshold that determines female reservation status. Columns (1)–(3) report competence measures based on standardized years of education benchmarked against: all citizens (1), citizens of the same group (2), and all citizens using husband's education in place of the candidate's own (3). Columns (4)–(6) report eliteness measures: an indicator for whether any household member holds a salaried government job (4); an indicator for whether any household member pays income or professional taxes (5); and a PCA-based wealth index constructed from land ownership, housing characteristics, and asset ownership (6). Panel A reports results for candidates; Panel B reports results for winners. All specifications include GP-level fixed effects and control for election year and GP-level covariates. Standard errors are clustered at the GP level and reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

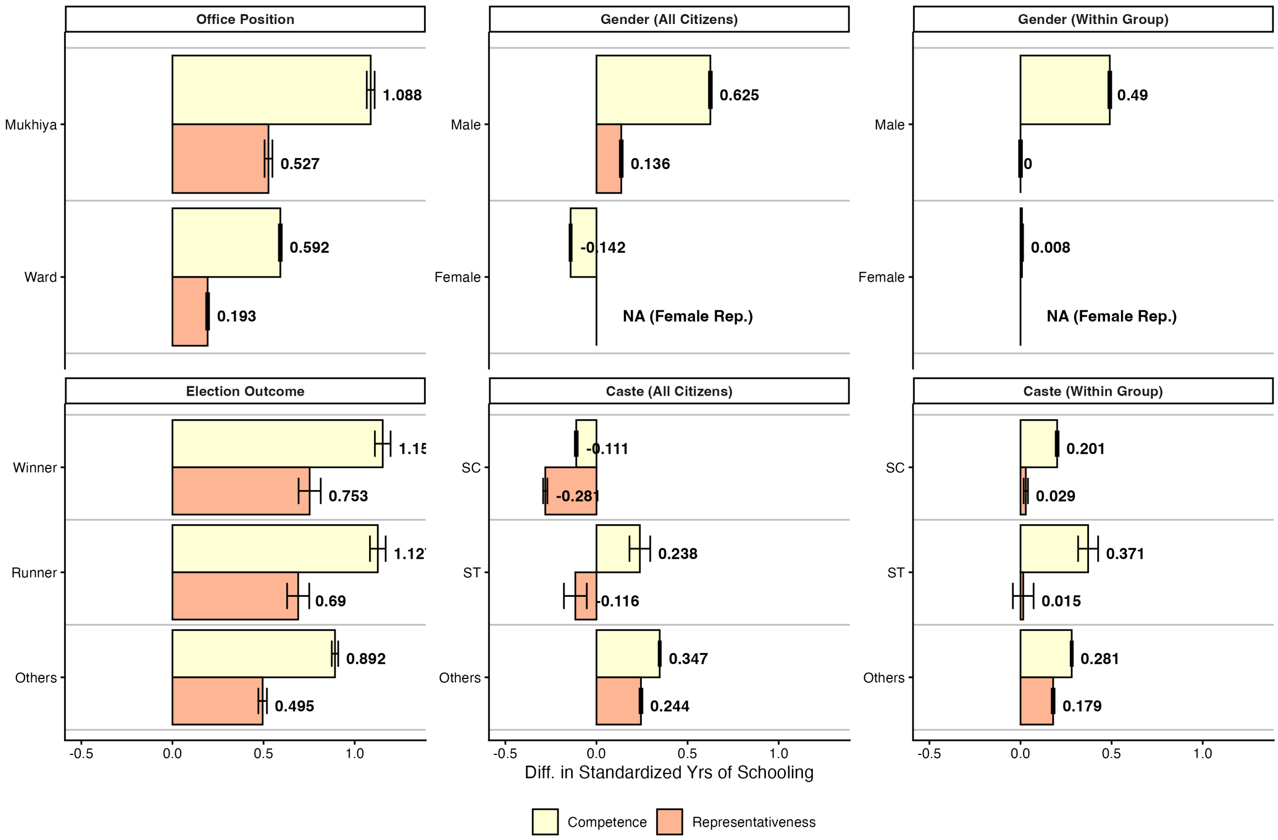
# 10 Figures

Figure 1: Political Selection: Competence and Representativeness




Notes: This figure visualizes the coefficients from the regressions reported in Table 1. Each bar represents the average difference in standardized years of education between candidates and the general population (Competence, yellow bars), and between candidates' fathers and the general population (Representativeness, orange bars). The "Baseline" specification includes GP fixed effects. Subsequent rows progressively add fixed effects for gender, age cohort, and caste group. The final row ("Gender + Household") utilizes household fixed effects to compare candidates to their own siblings. Error bars represent 95% confidence intervals; standard errors are clustered at the GP level.

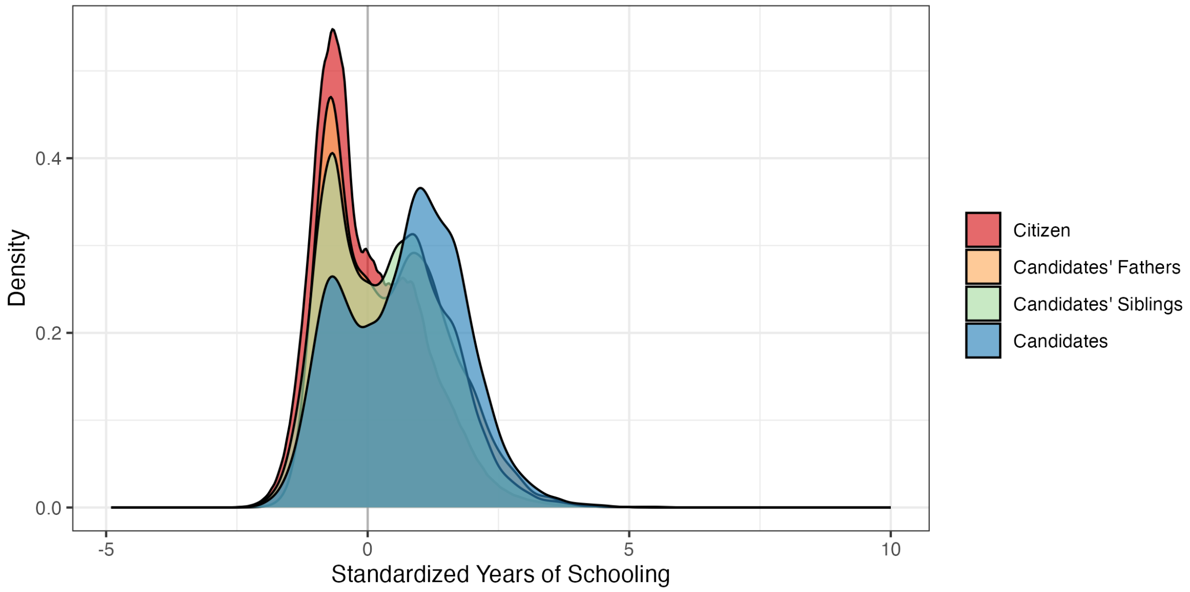
Figure 2: Heterogeneity in Selection



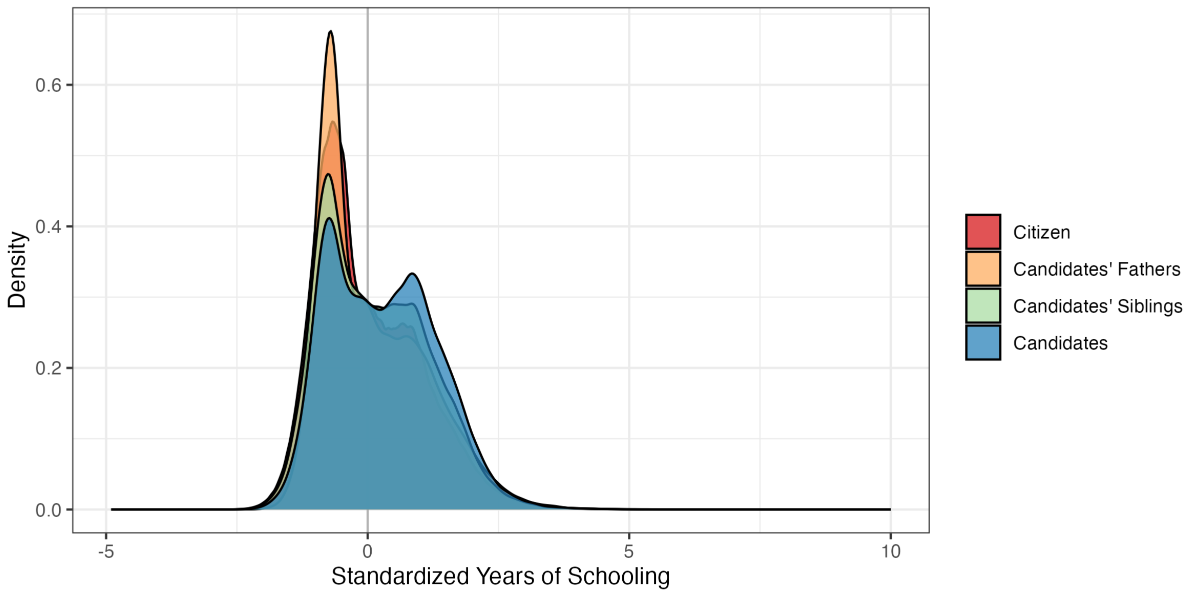

Notes: This figure plots coefficients from the baseline specifications (Equation 1 and **??**) across various sub-groups, with standardized years of education as the dependent variable. Top left compares candidates for GP head and Ward member positions against the general population. Top middle and Top right compare male and female candidates against the full population and their respective gender groups, respectively. Bottom left disaggregates candidates by election outcome (winners, runners-up, and other candidates) relative to the population. Bottom middle and Bottom right compare candidates from different caste categories (SC/ST and Others) against the full population and their own caste groups, respectively. All specifications include GP fixed effects. Error bars represent 95% confidence intervals with standard errors clustered at the GP level.

Figure 3: Candidates, Fathers & Siblings

(a) GP Head



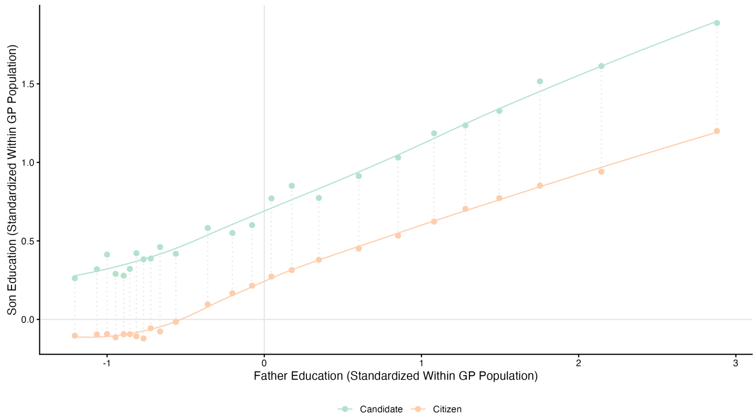

(b) Ward Member



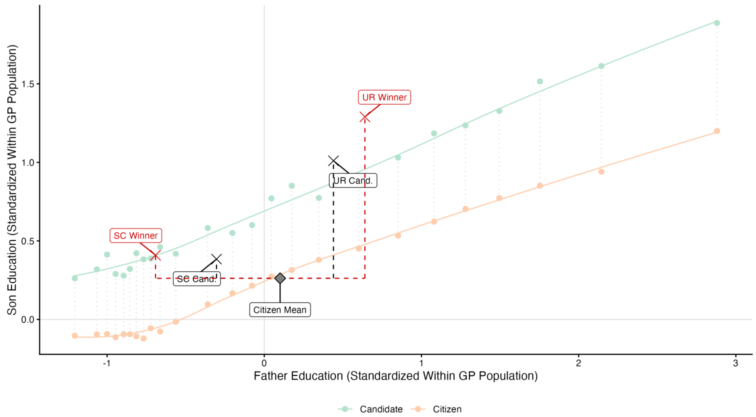

Notes: This figure plots the Kernel density of standardized years of education for candidates, their fathers, their siblings, and the general population. Years of education are standardized by gender, caste, and age cohort within each GP to account for local demographic differences. Panel A restricts the sample to candidates running for the position of GP heads and their respective family members. Panel B reports the same distributions for candidates running for Ward member positions and their families.

Figure 4: Competence-Representativeness Trade-off

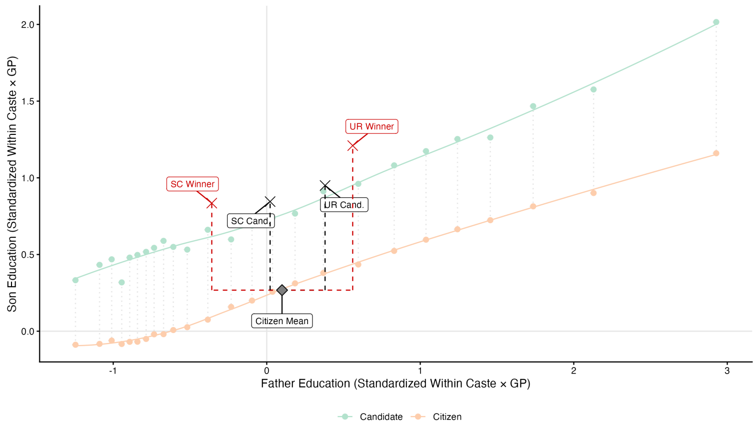
(a) The Candidate Selection Frontier and Citizen Mobility Curve




(b) Selection Frontier by Reservation Status




(c) Selection Frontier by Reservation Status (Caste-Benchmarked)




Notes: This figure plots intergenerational education mobility — father's education against son's education — for candidates and citizens in the SC reservation regression discontinuity sample. Bin scatter points are constructed by dividing the sample into 25 quantile bins based on father's education, with vertical bars indicating the within-bin range and smooth curves fitted separately for candidates and citizens. Panel (a) presents the baseline bin scatter without reference points, with years of education standardized within GP. Panel (b) augments Panel A by adding RD point estimates for mean father's and son's education among unreserved (UR) and SC candidates and winners, with the citizen mean shown as a diamond reference point; dashed lines indicate each group's deviation from the citizen mean along both dimensions. Panel (c) mirrors Panel B but benchmarks years of education within both GP and caste group, allowing comparisons relative to one's own caste peers. Black markers correspond to candidates; red markers correspond to winners.

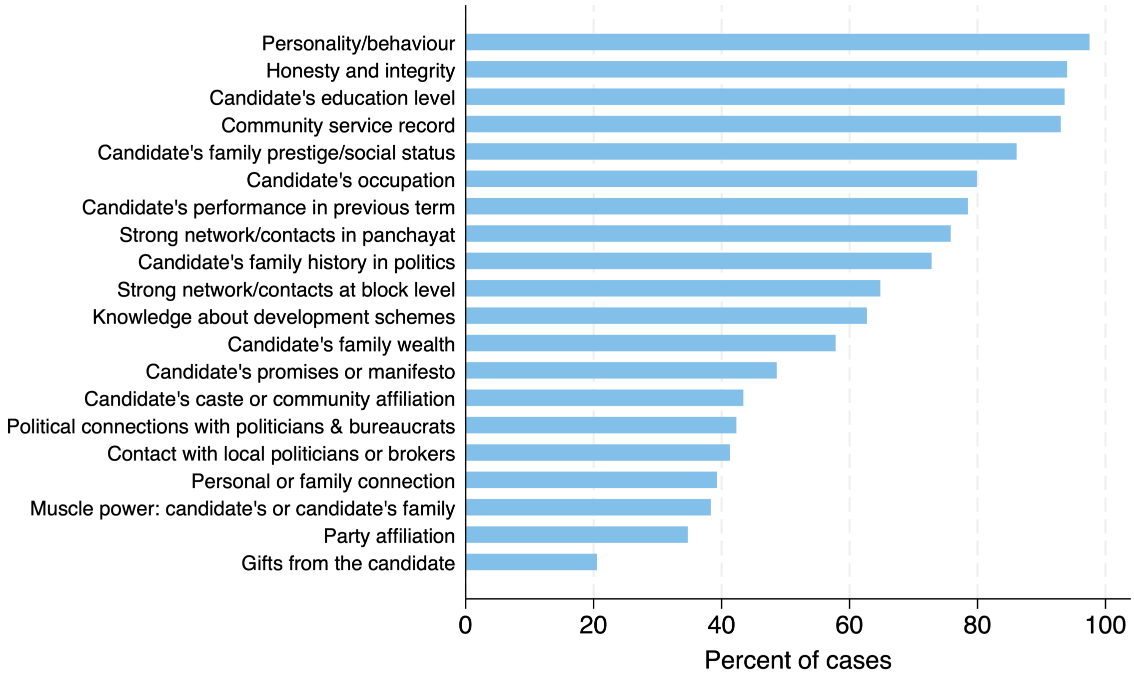
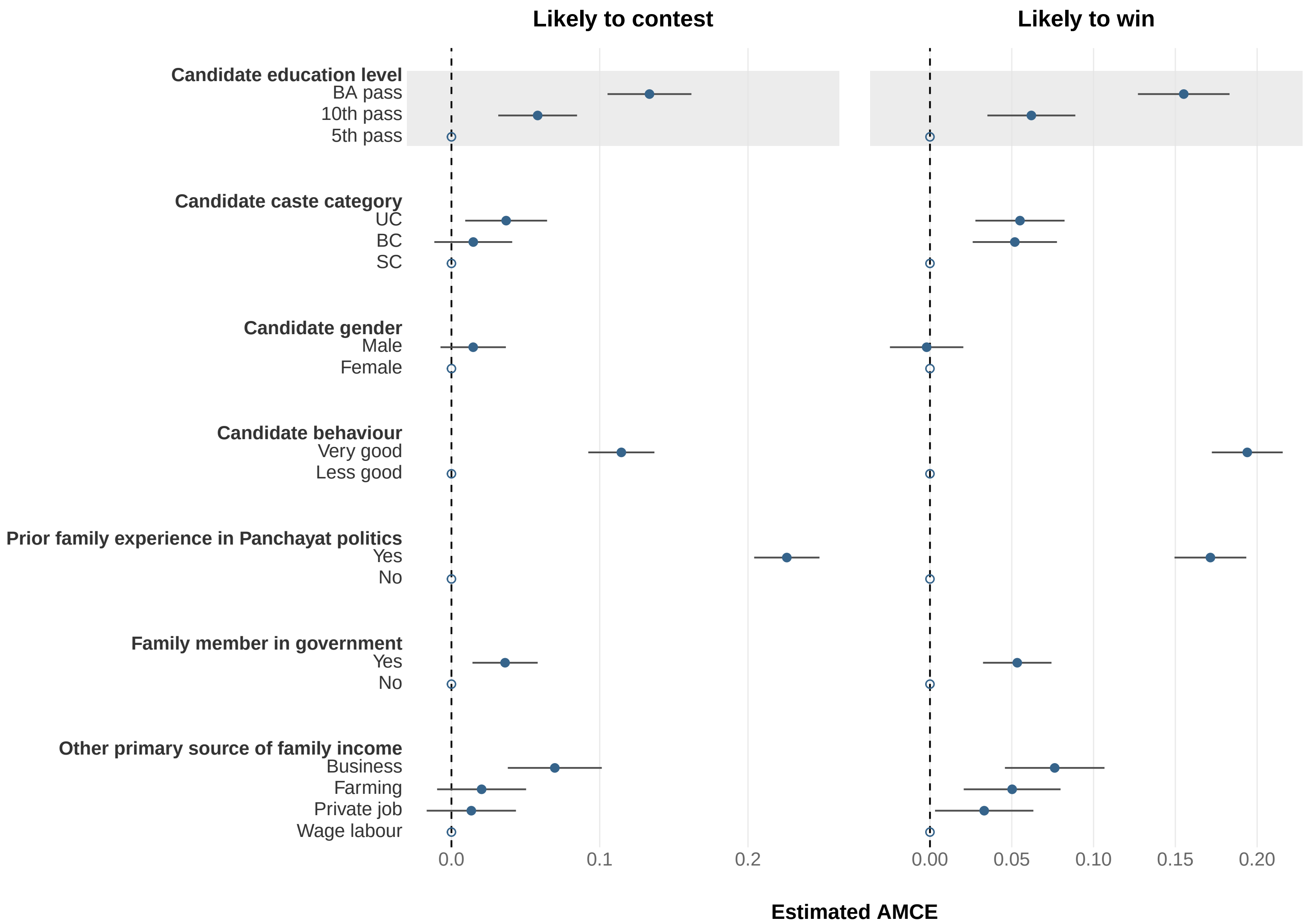


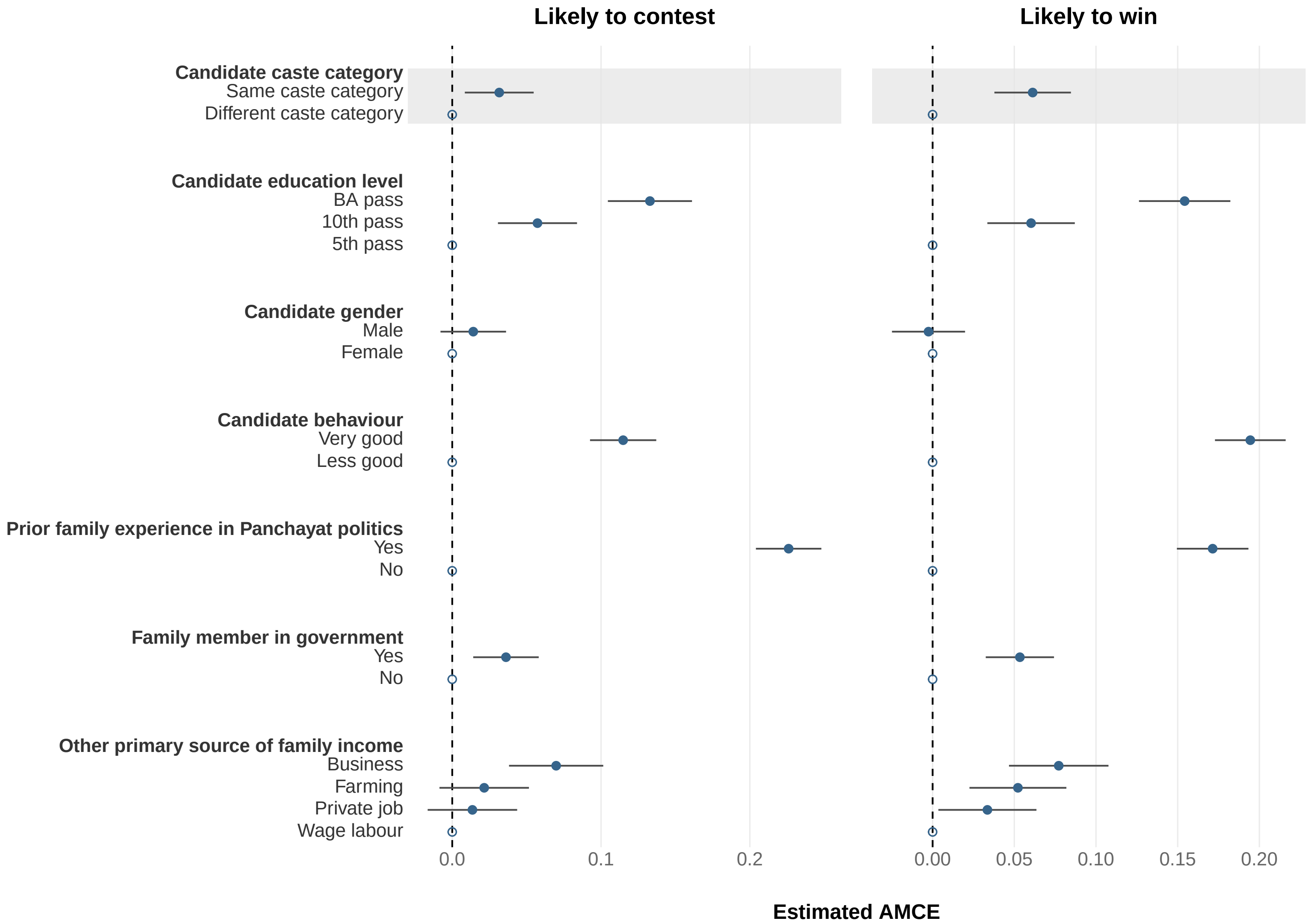

Figure 5: Qualities based on which citizens report evaluating Panchayat candidates: Percent of cases

Figure 6: Voter perceptions of likelihood of candidate type who contest and win




Notes: Bars represent 95% confidence intervals. Estimates are Average Marginal Component Effects (AMCEs) from a forced−choice conjoint experiment (N = 1,105 respondents; effective N = 7,600 profile evaluations). Source: Bihar Citizen Survey, February 2024.

Figure 7: Voter perceptions of likelihood of candidate type who contest and win (Candidate caste category recoded as per respondent caste category)




Notes: Bars represent 95% confidence intervals. Estimates are Average Marginal Component Effects (AMCEs) from a forced−choice conjoint experiment (N = 1,105 respondents; effective N = 7,600 profile evaluations). Source: Bihar Citizen Survey, February 2024.

# APPENDIX

## A Data and Construction

Table A1: Construction of GP-level Variables from SECC

| **Variable** | **Definition and Construction** |
|---|---|
| GP Asset Index | We construct a household-level asset index using six binary indicators: ownership of land; quality of housing (concrete roof and burnt brick or concrete walls); having four or more rooms; ownership of a phone; and ownership of a vehicle. Each asset is owned by at least 10% of households. The GP-level asset index is the average of this index across households in the GP. |
| Ethnic Fractionalisation | Measured as one minus the Herfindahl index of last names of household heads within a GP: $\text{FRACT}_g = 1 - \sum_{n=1}^{N} s_{ng}^2$, where $s_{ng}$ is the share of individuals with last name $n$ in GP $g$, and $N$ is the number of distinct last names. |
| Ethnic Polarisation | Constructed following **?**: $\text{POLAR}_g = 1 - \sum_{n=1}^{N} (0.5 - s_{ng})^2 s_{ng}/0.25$, where $s_{ng}$ is the share of individuals with last name $n$ in GP $g$. |
| Educational Mobility | For each GP, we measure educational mobility as the share of children aged 14–18 who completed primary education, restricting to households where parents have below primary education. |
| Land Gini | Measured as the Gini coefficient of total land owned across households within a GP. |
| Remoteness | Measured using census-derived data on the average distance of villages in the GP from the district headquarters. |

**Summary of Datasets**

| Dataset | Description | Analysis |
|---|---|---|
| Socioeconomic Caste Census (SECC), 2011–12 | A nationally administered census of households conducted by the Government of India. We use the rural Bihar sample, covering approximately 97 million individuals across 19 million households. The data provide rich individual- and household-level socioeconomic information and, crucially, allow us to link individuals to parents and other household members. | All analyses. Primary data source for competence and representativeness comparisons, GP-level covariates, and candidate–citizen matching. |
| Bihar State Election Commission Data, 2016 & 2021 | Administrative records on all candidates contesting GP head and ward member elections. The data cover 909,570 candidates across two election cycles (94,645 GP head and 268,591 ward candidates in 2016; 63,284 and 481,993 in 2021) and include detailed candidate characteristics, including years of education, age, gender, caste, father's name, votes received, and seat reservation status. | All analyses. Provides candidate-level data underlying all selection, close-election RD, and reservation RD results. |
| Gram Panchayat Development Plan (GPDP), 2024-25 | Annual Gram Panchayat Development Plans listing all proposed projects, with estimated costs and funding sources, based on ward- and Gram Sabha-level consultations. Scraped from eGramSwaraj (Ministry of Panchayati Raj), the data cover all GPs and provide project-level information on planned spending (e.g., roads, drains, piped water, solar streetlights). We combine these data with a survey of citizen preferences to measure the alignment between leader choices and citizen demand. | Effects of leader competence on policy alignment with citizen preferences (close-election RD); used jointly with citizen survey. |
| Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) MIS, 2016–2021 | Administrative data scraped from the Management Information System (MIS) reporting employment generated at the GP level under MGNREGA, which guarantees up to 100 days of wage employment per rural household per year. The data include total person-days and person-days by social group, including Scheduled Castes. We focus on outcomes between 2016 and 2021, corresponding to the tenure of GP heads elected in 2016. | Effects of leader competence on distributive policy outcomes (close-election RD). |
| Mission Antyodaya, 2019–20 | Village-level administrative data from the Ministry of Rural Development, Government of India (downloaded from SHRUG platform by **?**). The survey covers the near-universe of Bihar's approximately 37,262 revenue villages and provides detailed information on the availability of core public goods and services (e.g., infrastructure, basic amenities). | Effects of leader competence on skill-intensive policy outcomes (close-election RD). |
| Ward Member Survey (Bamezai et al. (2024), Baseline) | Baseline in-person survey conducted as part of a randomized evaluation of politician peer networks in Bihar. Over 7,700 elected ward members were surveyed in person across blocks statewide. The survey measures politicians' knowledge of rules and procedures for implementing government schemes (across domains including housing, infrastructure, and service delivery), their professional networks with higher-level officials (Block Development Officers, Block Panchayati Raj officials, GP heads), party support, and campaign characteristics. | Effects of education on scheme-implementation knowledge and bureaucratic networks (close-election RD on ward members); heterogeneous political selection by party affiliation. |
| Citizen Survey (Bamezai et al. (2024), Endline) | Endline phone survey conducted as part of a randomized evaluation of politician peer networks in Bihar. Approximately 10,000 citizens across 10 districts were asked to name up to two development schemes on which they would like their local government to increase spending. Responses are aggregated to construct GP$\times$scheme-level preference shares, separately for Scheduled Caste and non-SC populations. | Effects of leader competence on policy alignment with citizen preferences (close-election RD); used jointly with GPDP data. |

*Notes:* SECC and Bihar SEC linked via string-matching (Section 3.1, Appendix B; match rate $\approx$60.2% for unreserved GP head candidates). Education standardized within GP. Reservation strategies exploit population-based algorithms in Bihar SEC data (Appendix C). See Table A1 for GP-level variable definitions; Appendix F for survey details.

# B Additional Results / Extensions

Table A2: Political selection and village characteristics for male GP Heads

| | Years of Schooling | | | | | |
|---|---|---|---|---|---|---|
| | Wealth Score | Ethnic FRACT. | Ethnic POLAR. | Edu. Mobility | Gini Index Tot. Land | Distance District HQ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Competence - Comparison between Citizens and Candidates* | | | | | | |
| Candidate | 1.088$^{***}$ | 1.090$^{***}$ | 1.091$^{***}$ | 1.244$^{***}$ | 0.842$^{***}$ | 1.105$^{***}$ |
| | (0.011) | (0.010) | (0.011) | (0.039) | (0.144) | (0.023) |
| Candidate X Panchayat Feature | 0.009 | 0.034$^{**}$ | -0.033$^{***}$ | -0.327$^{***}$ | 0.284$^{*}$ | -0.001 |
| | (0.011) | (0.014) | (0.012) | (0.072) | (0.167) | (0.001) |
| Observations | 97,349,645 | 97,349,645 | 97,349,645 | 97,349,238 | 97,349,645 | 97,284,398 |
| *Panel B: Representativeness - Comparison between Citizens' and Candidates' Fathers* | | | | | | |
| Candidate's Father | 0.527$^{***}$ | 0.532$^{***}$ | 0.533$^{***}$ | 0.696$^{***}$ | -0.062 | 0.571$^{***}$ |
| | (0.011) | (0.011) | (0.011) | (0.038) | (0.131) | (0.022) |
| Cand. Father X Panchayat Feature | 0.017 | 0.066$^{***}$ | -0.052$^{***}$ | -0.353$^{***}$ | 0.682$^{***}$ | -0.001$^{**}$ |
| | (0.011) | (0.012) | (0.012) | (0.071) | (0.151) | (0.001) |
| Observations | 97,349,645 | 97,349,645 | 97,349,645 | 97,349,238 | 97,349,645 | 97,284,398 |

Notes: This table reports heterogeneity in political selection by village-level characteristics, using data from the 2016 and 2021 Panchayat elections. The dependent variable is years of schooling, standardized within Gram Panchayats. Panel A reports differences between candidates and citizens, while Panel B reports differences between candidates' fathers and citizens. Columns (1)–(6) interact an indicator for ever running for office with the following Gram Panchayat–level characteristics: average household wealth levels (1), ethnic fractionalization (2), ethnic polarization (3), educational mobility (4), land inequality (5), and distance from the Panchayat to the district headquarters (6). Standard errors are clustered at the Gram Panchayat level and reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A3: Effects of Political Competence on Scheme Knowledge and Solutions

| | Knowledge | | | | | | |
|---|---|---|---|---|---|---|---|
| | Avg. | Acct. | AWAS | NALIGALI | PDS | Pension | Solar Light |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Above Primary | 0.353** | 0.541** | 0.592*** | 0.135 | -0.533* | -0.188 | 0.409* |
| | (0.147) | (0.262) | (0.213) | (0.206) | (0.273) | (0.356) | (0.215) |
| Bandwidth | 0.10 | 0.11 | 0.09 | 0.15 | 0.12 | 0.11 | 0.13 |
| Control Mean | 1.95 | 2.56 | 1.75 | 1.35 | 2.50 | 2.70 | 1.51 |
| Observations | 911 | 949 | 814 | 1,141 | 431 | 388 | 1,023 |

This table reports the effects of electing a more educated GP Head—defined as having above-primary education—on politician's scheme Knowledge. Estimates are obtained from a close-election regression discontinuity design using the 2016 ward elections. The treatment variable (*Above Primary*) is a binary indicator equal to one if the winning candidate has above-primary education in the ward elections. Each WM was asked to list down steps to be undertaken to implement government schemes. The outcome variable is simply the number of steps a ward members is able to recount, matched to a predetermined checklist. Column (1) is the average score created using knowledge of the six schemes shown in columns (2)-(7). Column (2) is steps required to open the ward account, column (3) on housing (AWAS), column (4) drains, column (5) is the PDS, column (6) is pensions, column (7) is the solar light schemes. All dependent variables are standardized across GPs. Robust standard errors are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A4: Effects of Political Competence on Network and Party Connections

| | Network (Contact Info.) | | | | Party | |
|---|---|---|---|---|---|---|
| | Mukhiya | Panchayat Secretary | BPRO | BDO | Party Involvement | Political Support |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Above Primary | 0.095 | 0.264** | 0.115 | 0.283** | 0.133* | 0.054** |
| | (0.068) | (0.114) | (0.093) | (0.112) | (0.080) | (0.024) |
| Bandwidth | 0.15 | 0.13 | 0.18 | 0.11 | 0.11 | 0.07 |
| Control Mean | 0.91 | 0.73 | 0.28 | 0.33 | 0.17 | 0.05 |
| Observations | 1,242 | 1,100 | 1,456 | 951 | 953 | 681 |

This table reports the effects of electing a more educated Ward members—defined as having above-primary education—on politician's network and party connections. The data uses responses from a survey of male ward members. Estimates are obtained from a close-election regression discontinuity design using the 2021 ward elections. The treatment variable (*Above Primary*) is a binary indicator equal to one if the ward winner has above-primary education in the Ward election. Columns (1)–(4) examine political network outcomes, measured by whether the respondent knows the phone number of the GP Head (1), Panchayat Secretary (2), Block Panchayat Raj Officer (BPRO) (3), and Block Development Officer (BDO) (4). Columns (5)–(6) examine Ward members' party connections, measured by indicators for any party involvement (5) and receipt of political support (6). Robust standard errors are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A5: Political Selection Candidate's Social Groups

| | Avg. Years of Schooling | | | |
|---|---|---|---|---|
| | Age Cohort (1) | Caste (2) | Surname (3) | GenderXAgeXSurname (4) |
| Candidate | 0.071*** | 0.022*** | 0.108*** | 0.366*** |
| | (0.001) | (0.000) | (0.001) | (0.002) |
| Observations | 97,349,674 | 97,349,674 | 97,349,674 | 97,349,674 |

This table reports the extent to which politicians come from more educated social groups relative to the average citizen. The outcome variable in each column is the average years of schooling of the social group to which each individual belongs: age cohort (1), caste group (2), surname group (3), and gender × age cohort × surname group (4). The coefficient on the candidate indicator captures how much more educated the average politician's social group is relative to that of the average citizen. All specifications include GP-level fixed effects. Standard errors are clustered at the GP level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Political selection, level of office and electoral performance

| | Years of Education | | | |
|---|---|---|---|---|
| | All Candidates (1) | Winner (2) | Runner (3) | Others (4) |
| | *Panel A: Mukhiya Candidates* | | | |
| Candidates | 1.088*** | 1.417*** | 1.401*** | 1.099*** |
| | (0.011) | (0.026) | (0.026) | (0.011) |
| Observations | 97,349,648 | 97,349,648 | 97,349,648 | 97,349,648 |
| | *Panel B: Ward Candidates* | | | |
| Candidates | 0.592*** | 0.690*** | 0.610*** | 0.627*** |
| | (0.004) | (0.007) | (0.007) | (0.005) |
| Citizen Mean | 3.457 | 3.460 | 3.460 | 3.457 |
| Citizen SD | 3.981 | 3.983 | 3.983 | 3.981 |
| Observations | 97,349,648 | 97,349,648 | 97,349,648 | 97,349,648 |

The table describes the political selection in Bihar for electoral candidates competing for unreserved seats. Panel A shows the results for Mukhiya candidates, while panel B shows the results for Ward Candidates. The dependent variables are years of education, normalized by substracting the population mean and divided by standard deviation respectively within each GP. Column (1) presents the difference in years of education between all electoral candidates and citizens. Column (2)-(4) further breaks down the analysis by winner, runner and all other candidates respectively. Standard errors are clustered at GP level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Effects of SC Reservation on Selection for Mukhiya Candidates (including female)

| | Yrs of Schooling | Representativeness | | | |
|---|---|---|---|---|---|
| | Candidate Edu Yrs | Gov. Job | Income Tax | Wealth Score | Father Edu Yrs |
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: Comparison to all citizen* | | | | | |
| SC RSVN | -0.630$^{***}$ | -0.148$^{***}$ | -0.240$^{***}$ | -0.650$^{***}$ | -0.738$^{***}$ |
| | (0.039) | (0.034) | (0.038) | (0.033) | (0.051) |
| Dep. Mean | 0.67 | 0.24 | 0.19 | 0.51 | 0.44 |
| Bandwidth | 400.686 | 613.649 | 416.315 | 489.966 | 161.306 |
| Observations | 37,810 | 51,338 | 38,785 | 43,449 | 6,478 |
| *Panel B: Comparison to citizen of own group* | | | | | |
| SC RSVN | -0.121$^{***}$ | -0.002 | -0.092$^{**}$ | -0.165$^{***}$ | -0.350$^{***}$ |
| | (0.041) | (0.037) | (0.039) | (0.034) | (0.053) |
| Dep. Mean | 0.62 | 0.23 | 0.17 | 0.45 | 0.38 |
| Bandwidth | 406.693 | 542.187 | 486.262 | 486.586 | 162.027 |
| Observations | 38,124 | 46,552 | 41,667 | 43,203 | 6,508 |

This table reports the effects of female reservation on political selection outcomes for Mukhiya candidates and winners in the 2016 and 2021 Panchayat elections, extending the main analysis to include female-reserved seats. Estimates are obtained from a regression discontinuity design exploiting the population threshold that determines female reservation status. Columns (1)–(3) report competence measures based on standardized years of education benchmarked against: all citizens (1), citizens of the same group (2), and all citizens using husband's education in place of the candidate's own (3). Columns (4)–(6) report eliteness measures: an indicator for whether any household member holds a salaried government job (4); an indicator for whether any household member pays income or professional taxes (5); and a PCA-based wealth index constructed from land ownership, housing characteristics, and asset ownership (6). Panel A reports results for candidates; Panel B reports results for winners. All specifications include GP-level fixed effects and control for election year and GP-level covariates. Standard errors are clustered at the GP level and reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A8: Effects of Reservation on Political Selection for Mukhiya Winners

| | Yrs of Schooling | Representativeness | | | |
|---|---|---|---|---|---|
| | Candidate Edu Yrs | Gov. Job | Income Tax | Wealth Score | Father Edu Yrs |
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: Comparison to all citizen* | | | | | |
| SC RSVN | -0.881$^{***}$ | -0.527$^{***}$ | -0.812$^{***}$ | -1.040$^{***}$ | -1.332$^{***}$ |
| | (0.121) | (0.145) | (0.137) | (0.106) | (0.119) |
| Dep. Mean | 1.29 | 0.38 | 0.40 | 0.92 | 0.64 |
| Bandwidth | 172.877 | 163.254 | 261.318 | 215.440 | 197.064 |
| Observations | 1,094 | 1,054 | 1,548 | 1,339 | 722 |
| *Panel B: Comparison to citizen of own group* | | | | | |
| SC RSVN | -0.375$^{***}$ | -0.465$^{***}$ | -0.776$^{***}$ | -0.542$^{***}$ | -0.918$^{***}$ |
| | (0.125) | (0.155) | (0.161) | (0.135) | (0.134) |
| Dep. Mean | 1.21 | 0.36 | 0.38 | 0.85 | 0.56 |
| Bandwidth | 191.133 | 173.623 | 238.573 | 176.391 | 201.106 |
| Observations | 1,186 | 1,089 | 1,373 | 1,103 | 742 |

This table reports the effects of Scheduled Caste (SC) reservation on political selection outcomes for Mukhiya winners in the 2016 and 2021 Panchayat elections. Estimates are obtained from a regression discontinuity design around the population threshold for SC reservation. Columns (1)–(5) report results for the following candidate-level outcomes: standardized years of education (1); an indicator for whether any household member holds a salaried government job (2); an indicator for whether any household member pays income or professional taxes (3); a PCA-based wealth index constructed using land ownership, housing characteristics, and asset ownership (4); and the candidate's father's years of education (5). Panel A reports outcomes standardized relative to all citizens within the GP, while Panel B reports outcomes standardized relative to individuals from the same caste within the GP. The sample is restricted to seats unreserved for women. All specifications include block fixed effects and election-year controls. Standard errors are clustered at the GP level and reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A9: Effects of Female Reservation on Political Selection By Caste

| | Yrs of Schooling | | Representativeness | | | |
|---|---|---|---|---|---|---|
| | Candidate Edu Yrs | Husband Edu Yrs | Gov. Job | Income Tax | Wealth Score | Highest HH Edu Yrs |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Unreserved* | | | | | | |
| Female RSVN | -0.794*** | -0.154*** | -0.062 | -0.085* | -0.094** | -0.117*** |
| | (0.038) | (0.052) | (0.046) | (0.045) | (0.038) | (0.033) |
| Bandwidth | 1010.17 | 921.52 | 918.68 | 980.92 | 1039.18 | 969.56 |
| Observations | 19,001 | 14,367 | 18,239 | 18,739 | 19,304 | 30,264 |
| *Panel B: SC Reserved* | | | | | | |
| Female RSVN | -0.738*** | -0.101 | -0.121** | -0.062 | -0.115** | -0.174*** |
| | (0.050) | (0.078) | (0.051) | (0.042) | (0.047) | (0.043) |
| Bandwidth | 157.45 | 106.49 | 144.01 | 161.70 | 156.72 | 149.62 |
| Observations | 8,072 | 4,890 | 7,621 | 8,206 | 8,064 | 11,936 |
| *Panel C: OBC Reserved* | | | | | | |
| Female RSVN | -0.833*** | -0.162** | -0.028 | -0.029 | -0.038 | 0.011 |
| | (0.047) | (0.064) | (0.047) | (0.041) | (0.051) | (0.043) |
| Bandwidth | 304.09 | 150.04 | 308.62 | 405.56 | 292.42 | 266.20 |
| Observations | 5,987 | 2,695 | 6,046 | 7,603 | 5,774 | 8,846 |

This table shows the effects of female reservation on candidate competence, in terms of education background. Only 2016 candidates are included in the sample. We collapse the data into GP level and respectively calculate the average (standardized) education level of candidates within the same GP. In column (1)-(4), we are comparing the average education level of candidates from reserved GPs and those from unreserved GPs, while in column (5)-(8), only GPs with at least 1 female candidate running is included, and we are comparing the average education level of female candidates from reserved GPs and female candidates from unreserved GPs. The running variable 'Population Diff.' represents the difference between the Gram Panchayat population and the cutoff population size (the population cutoff line is calculated by taking the average population size between the last reserved Gram Panchayat and the first unreserved Gram Panchayat). Controls include fixed effects on election year. Standard errors are clustered at Block level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# C RD Design Validation

Table A10: SC Reservation Balance Test

| | Control Mean | RD Estimate | Obs | $p$-value (FDR $q$-value) |
|---|---|---|---|---|
| Paved Road (Census 2001) | 1.78 | -0.20 | 4,463 | 0.16 (1) |
| Bank Facilities (Census 2001) | 0.34 | 0.03 | 5,410 | 0.56 (1) |
| Bus facilities (Census 2001) | 0.54 | 0.04 | 5,015 | 0.65 (1) |
| Child Welfare Centre (Census 2001) | 0.05 | 0.28 | 6,111 | 0 (0) |
| Distance District HQ | 31.88 | 0.21 | 4,647 | 0.76 (1) |
| Total Educational Facilities (Census 2001) | 3.46 | -0.06 | 5,318 | 0.68 (1) |
| Education Mobility | 0.46 | 0.01 | 4,727 | 0.47 (1) |
| Ethnic Fractionalization | 0.89 | 0.00 | 4,774 | 0.85 (1) |
| Ethnic Polarization | 0.34 | -0.01 | 4,340 | 0.16 (1) |
| Medical Facility (Census 2001) | 0.88 | 0.05 | 5,458 | 0.58 (1) |
| Middle School Facility (Census 2001) | 1.21 | -0.05 | 4,632 | 0.62 (1) |
| Distance Nearest Statutory Town | 20.65 | 1.08 | 4,906 | 0.05 (0.6) |
| Wealth Score | 0.00 | 0.02 | 4,613 | 0.82 (1) |
| Phone Lines (Census 2001) | 0.54 | 0.07 | 4,831 | 0.3 (1) |
| Primary Health Sub Centres (Census 2001) | 0.43 | 0.08 | 4,510 | 0.18 (1) |
| Post Office (Census 2001) | 1.03 | -0.05 | 4,590 | 0.52 (1) |
| Power Supply (Census 2001) | 1.67 | 0.05 | 4,133 | 0.74 (1) |
| Tank (Census 2001) | 0.52 | 0.05 | 5,914 | 0.6 (1) |
| Tap Water (Census 2001) | 0.15 | -0.11 | 5,037 | 0.01 (0.12) |
| Mean Village Income (Census 2001) | 434,692.63 | 41,417.58 | 4,225 | 0.84 (1) |
| Mean Village Income (Census 2001) | 457,166.91 | -2,114,289.00 | 2,618 | 0.27 (1) |
| Well (Census 2001) | 0.82 | 0.05 | 4,479 | 0.07 (0.67) |
| Gini Index (Total Land) | 0.87 | 0.00 | 3,942 | 0.84 (1) |
| Gini Index (Irrigated Land) | 0.88 | 0.00 | 4,266 | 0.81 (1) |

This table reports balance tests for the SC reservation regression discontinuity design. For each baseline GP-level covariate, we estimate the RD coefficient using the SC population recentered around block-specific reservation thresholds as the running variable, with SC reservation status as the treatment, and block-level fixed effects as covariates. The mean of each covariate is reported for unreserved GPs within the optimal bandwidth. Standard errors are clustered at the GP level. The final column reports sharpened q-values following the Benjamini, Krieger, and Yekutieli (2006) procedure to account for multiple hypothesis testing.

Table A11: SC Reservation Balance Test (Female Unreserved)

| | Control Mean | RD Estimate | Obs | $p$-value (FDR $q$-value) |
|---|---|---|---|---|
| Paved Road (Census 2001) | 1.73 | 0.04 | 2,410 | 0.78 (1) |
| Bank Facilities (Census 2001) | 0.32 | 0.05 | 1,936 | 0.51 (0.78) |
| Bus facilities (Census 2001) | 0.51 | 0.18 | 2,518 | 0.07 (0.21) |
| Child Welfare Centre (Census 2001) | 0.05 | 0.06 | 2,509 | 0.12 (0.28) |
| Distance District HQ | 32.01 | 0.57 | 3,101 | 0.42 (0.71) |
| Total Educational Facilities (Census 2001) | 3.42 | 0.02 | 2,215 | 0.89 (1) |
| Education Mobility | 0.46 | 0.00 | 2,342 | 0.81 (1) |
| Ethnic Fractionalization | 0.89 | 0.01 | 2,560 | 0.02 (0.09) |
| Ethnic Polarization | 0.34 | -0.03 | 2,892 | 0 (0.01) |
| Medical Facility (Census 2001) | 0.88 | 0.05 | 2,176 | 0.62 (1) |
| Middle School Facility (Census 2001) | 1.19 | 0.04 | 2,441 | 0.69 (1) |
| Distance Nearest Statutory Town | 20.76 | 0.92 | 2,187 | 0.14 (0.28) |
| Wealth Score | -0.02 | -0.03 | 2,283 | 0.7 (1) |
| Phone Lines (Census 2001) | 0.52 | 0.19 | 2,401 | 0.02 (0.09) |
| Primary Health Sub Centres (Census 2001) | 0.44 | 0.06 | 2,016 | 0.42 (0.71) |
| Post Office (Census 2001) | 1.01 | 0.00 | 2,174 | 1 (1) |
| Power Supply (Census 2001) | 1.63 | -0.03 | 2,842 | 0.86 (1) |
| Tank (Census 2001) | 0.53 | -0.16 | 2,355 | 0.11 (0.28) |
| Tap Water (Census 2001) | 0.16 | -0.13 | 2,888 | 0.01 (0.06) |
| Mean Village Income (Census 2001) | 369,680.78 | 1,218,851.90 | 1,950 | 0 (0) |
| Mean Village Income (Census 2001) | 570,399.00 | 224,651,072.00 | 1,212 | 0.45 (0.71) |
| Well (Census 2001) | 0.82 | -0.04 | 2,301 | 0.74 (1) |
| Gini Index (Total Land) | 0.87 | 0.01 | 3,086 | 0.01 (0.07) |
| Gini Index (Irrigated Land) | 0.88 | 0.01 | 2,266 | 0.08 (0.21) |

Table A12: Gender Reservation Balance Test

| | Control Mean | RD Estimate | Obs | $p$-value (FDR $q$-value) |
|---|---|---|---|---|
| Paved Road (Census 2001) | 1.76 | -0.05 | 5,325 | 0.55 (1) |
| Bank Facilities (Census 2001) | 0.32 | -0.04 | 5,354 | 0.27 (1) |
| Bus facilities (Census 2001) | 0.53 | -0.12 | 5,351 | 0.03 (0.24) |
| Child Welfare Centre (Census 2001) | 0.05 | 0.03 | 5,349 | 0.22 (1) |
| Distance District HQ | 31.89 | 0.20 | 5,248 | 0.64 (1) |
| Total Educational Facilities (Census 2001) | 3.56 | -0.11 | 5,521 | 0.24 (1) |
| Education Mobility | 0.46 | 0.00 | 5,205 | 0.58 (1) |
| Ethnic Fractionalization | 0.89 | 0.00 | 5,263 | 0.68 (1) |
| Ethnic Polarization | 0.34 | 0.00 | 5,304 | 0.82 (1) |
| Medical Facility (Census 2001) | 0.90 | -0.02 | 5,298 | 0.72 (1) |
| Middle School Facility (Census 2001) | 1.16 | 0.04 | 5,316 | 0.47 (1) |
| Distance Nearest Statutory Town | 20.64 | -0.10 | 5,253 | 0.79 (1) |
| Wealth Score | -0.06 | 0.06 | 5,200 | 0.2 (1) |
| Phone Lines (Census 2001) | 0.51 | 0.00 | 5,348 | 0.93 (1) |
| Primary Health Sub Centres (Census 2001) | 0.44 | 0.01 | 5,351 | 0.81 (1) |
| Post Office (Census 2001) | 0.98 | -0.04 | 5,337 | 0.4 (1) |
| Power Supply (Census 2001) | 1.70 | -0.26 | 5,305 | 0 (0.06) |
| Tank (Census 2001) | 0.55 | 0.02 | 5,351 | 0.76 (1) |
| Tap Water (Census 2001) | 0.16 | 0.00 | 5,495 | 0.88 (1) |
| Mean Village Income (Census 2001) | 400,185.47 | -17,207.46 | 5,235 | 0.86 (1) |
| Mean Village Income (Census 2001) | 490,421.59 | 32,917.38 | 5,380 | 0.8 (1) |
| Well (Census 2001) | 0.83 | -0.06 | 5,488 | 0 (0) |
| Gini Index (Total Land) | 0.87 | 0.00 | 5,204 | 0.27 (1) |
| Gini Index (Irrigated Land) | 0.88 | 0.00 | 5,226 | 0.21 (1) |

This table reports balance tests for the female reservation regression discontinuity design. For each baseline GP-level covariate, we estimate the RD coefficient using the female population recentered around block-specific reservation thresholds as the running variable, with female reservation status as the treatment, and controlling for caste reservation status and block-level fixed effects. The mean of each covariate is reported for non-female-reserved GPs within the optimal bandwidth. Standard errors are clustered at the GP level. The final column reports sharpened q-values following the Benjamini, Krieger, and Yekutieli (2006) procedure to account for multiple hypothesis testing.

Table A13: Mukhiya Close-Election Balance Test

| | Control Mean | RD Estimate | Obs | $p$-value (FDR $q$-value) |
|---|---|---|---|---|
| Candidate Father Edu | 5.30 | -0.17 | 354 | 0.91 (1) |
| Paved Road (Census 2001) | 1.78 | 0.08 | 2,560 | 0.64 (1) |
| Bank Facilities (Census 2001) | 0.34 | 0.06 | 2,544 | 0.35 (1) |
| Bus facilities (Census 2001) | 0.59 | 0.08 | 2,440 | 0.47 (1) |
| Child Welfare Centre (Census 2001) | 0.06 | -0.05 | 2,394 | 0.29 (1) |
| Distance District HQ | 32.12 | -0.04 | 2,414 | 0.98 (1) |
| Total Educational Facilities (Census 2001) | 3.45 | -0.14 | 2,153 | 0.59 (1) |
| Education Mobility | 0.46 | 0.01 | 2,449 | 0.68 (1) |
| Ethnic Fractionalization | 0.89 | 0.00 | 2,092 | 0.74 (1) |
| Ethnic Polarization | 0.34 | 0.00 | 2,037 | 0.93 (1) |
| Medical Facility (Census 2001) | 0.88 | 0.22 | 2,598 | 0.07 (1) |
| Middle School Facility (Census 2001) | 1.24 | -0.07 | 2,374 | 0.55 (1) |
| Distance Nearest Statutory Town | 20.40 | -0.74 | 2,180 | 0.63 (1) |
| Wealth Score | -0.04 | 0.09 | 2,449 | 0.44 (1) |
| Phone Lines (Census 2001) | 0.54 | -0.05 | 1,910 | 0.64 (1) |
| Primary Health Sub Centres (Census 2001) | 0.44 | 0.04 | 2,240 | 0.62 (1) |
| Post Office (Census 2001) | 1.04 | -0.25 | 2,167 | 0.02 (1) |
| Power Supply (Census 2001) | 1.66 | -0.38 | 2,177 | 0.17 (1) |
| Tank (Census 2001) | 0.52 | -0.02 | 2,227 | 0.89 (1) |
| Tap Water (Census 2001) | 0.16 | -0.11 | 2,246 | 0.13 (1) |
| Mean Village Income (Census 2001) | 288,080.00 | 199,424.03 | 2,123 | 0.49 (1) |
| Mean Village Income (Census 2001) | 413,981.06 | 290,817.31 | 2,445 | 0.5 (1) |
| Well (Census 2001) | 0.82 | 0.06 | 2,120 | 0.23 (1) |
| Gini Index (Total Land) | 0.87 | 0.00 | 2,476 | 0.77 (1) |
| Gini Index (Irrigated Land) | 0.88 | 0.00 | 2,413 | 0.82 (1) |

This table reports balance tests for the close-election regression discontinuity design. For each baseline GP-level covariate, we estimate the RD coefficient using the margin of victory of the more-educated candidate over the less-educated candidate as the running variable. The mean of each covariate is reported for GPs where the less-educated candidate won within the optimal bandwidth. Standard errors are clustered at the GP level. The final column reports sharpened q-values following the Benjamini, Krieger, and Yekutieli (2006) procedure to account for multiple hypothesis testing.

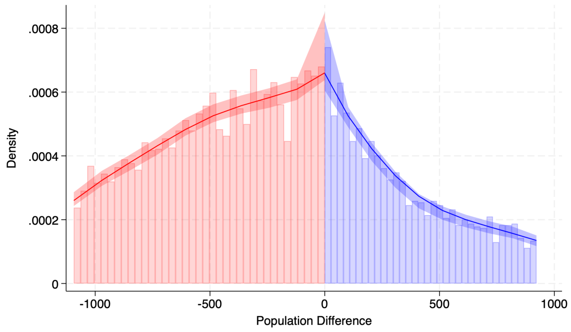
Table A14: Balance Test: Diff in Candidate Characteristics in Close Election - Ward

| | N | Dep. Mean | Winner/se |
|---|---|---|---|
| Scheduled Caste | 14944 | .22 | .0156** |
| | | | (.00681) |
| Scheduled Tribe | 14944 | .01 | .00295 |
| | | | (.00193) |
| Other Caste | 14944 | .77 | -.0186*** |
| | | | (.00696) |
| Woman | 14944 | .47 | -.045*** |
| | | | (.0082) |
| Age | 14943 | 38.86 | -1.03*** |
| | | | (.173) |
| Gov. Job | 13038 | .10 | -.0173 |
| | | | (.0211) |
| Salaried Job | 13034 | .09 | -.0122 |
| | | | (.0206) |
| Income Tax | 13026 | .07 | -.0285 |
| | | | (.0203) |
| Income High | 13033 | .10 | -.0226 |
| | | | (.0205) |
| Wealth Score | 13037 | .27 | -.00302 |
| | | | (.019) |
| Ag. Equipment | 13025 | .08 | .00598 |
| | | | (.0221) |
| Tot. Land | 13044 | .10 | .0178 |
| | | | (.0191) |
| Father Edu Yrs | 3868 | 4.10 | -.146 |
| | | | (.145) |

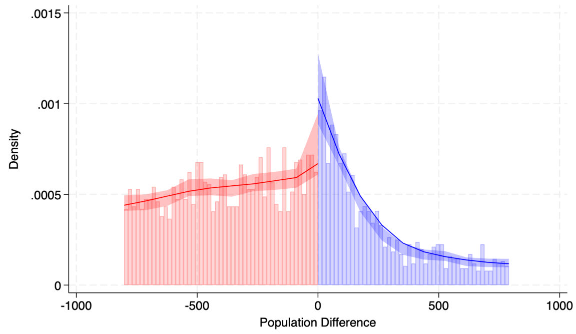
This table shows means of candidates characteristics in column (2) and differences around cutoff in column (3). Only 2021 Ward winners and runners that meet the sample restriction are included (below and above primary education cutoffs). Age is winsorized at top and bottom 1 percentile. Household-level characteristics and father education are only available for matched candidates. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Figure A1: McCrary tests for manipulation of the running variable

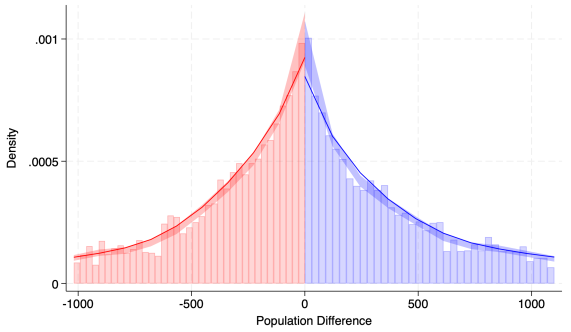
(a) SC Reservation RD (All Seats)



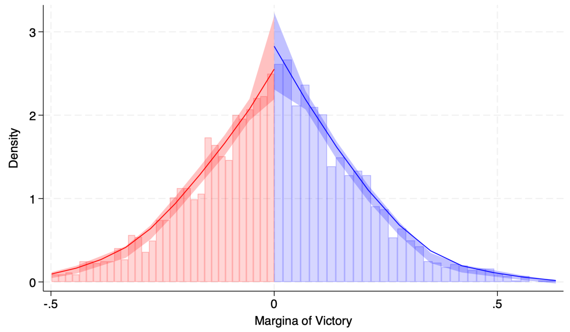

(b) SC Reservation RD (Female-Unreserved Only)




(c) Female Reservation RD




(d) Close-election Education RD




Notes: This figure presents McCrary density tests for manipulation of the running variable for each regression discontinuity design used in the paper. Panel (a) and Panel (b) use the SC population recentered around block-specific reservation thresholds as the running variable; Panel (a) includes all seats while Panel (b) restricts to female-unreserved seats only. Panel (c) uses the female population recentered around block-specific reservation thresholds. Panel (d) uses the margin of victory of the more-educated candidate minus the margin of victory of the less-educated candidate. The construction of each running variable is detailed in the main text.

# D Robustness Checks

Figure A2: Main Results by Alternative Matching Rates

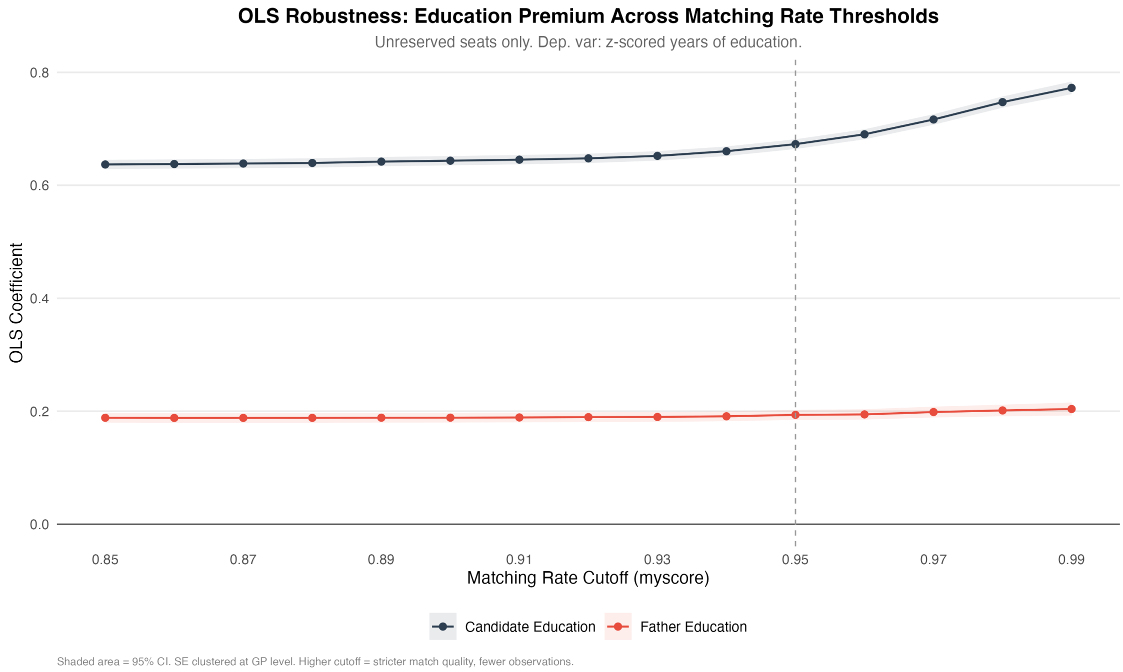



Figure A3: SC Reservation Main Results with Alternative BandWidth Selection

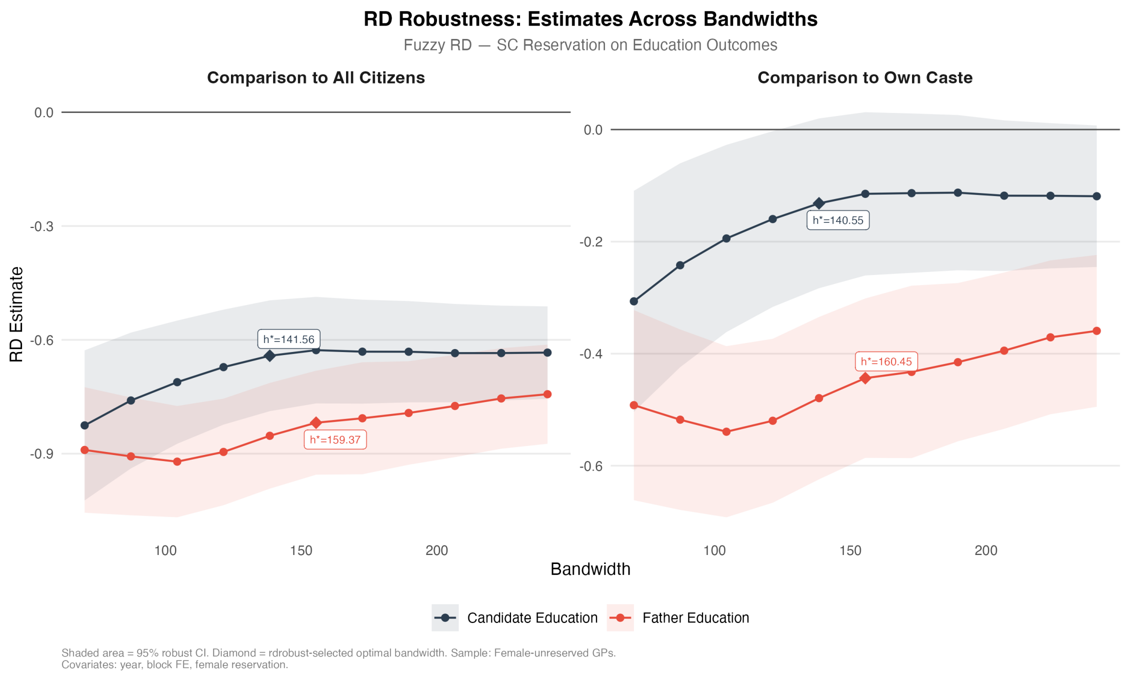


Figure A4: Female Reservation Main Results with Alternative BandWidth Selection

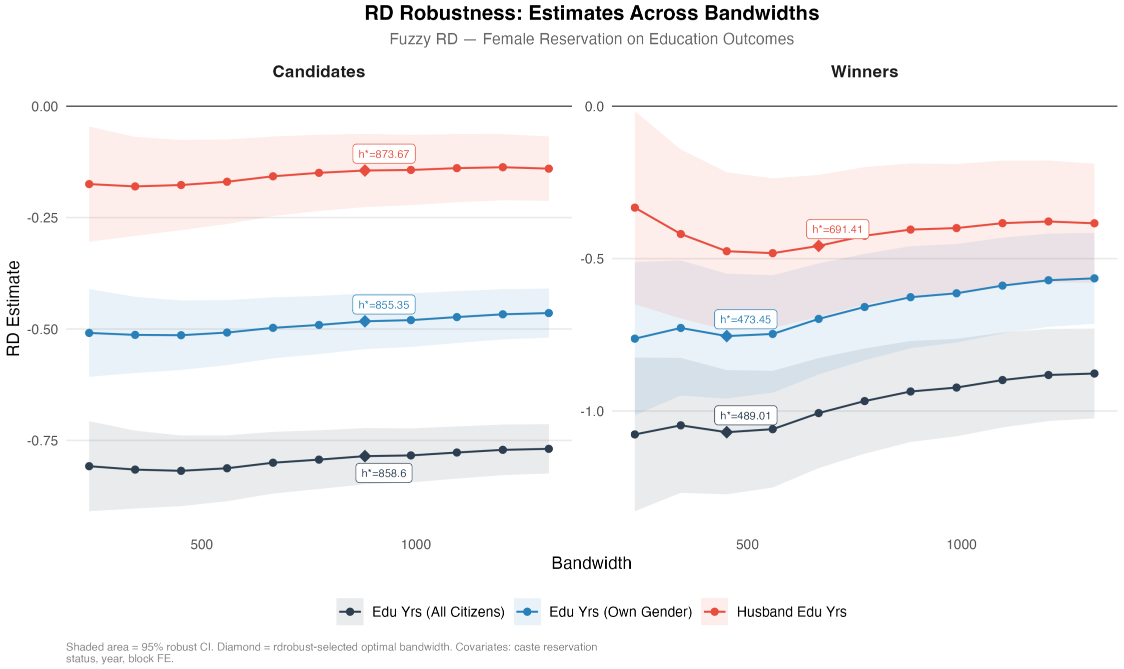



Figure A5: Close-Election Citizen Preference Outcomes with Alternative BandWidth Selection

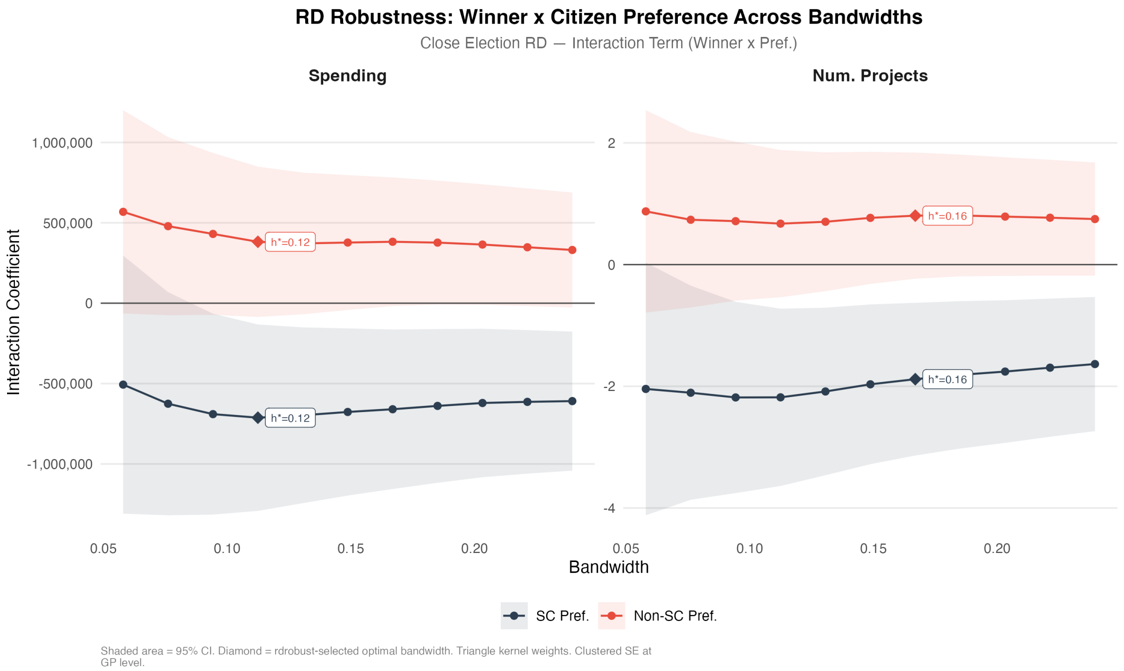


Table A15: Effects of Political Competence on Scheme Knowledge and Solutions

| | Knowledge | | | | | | |
|---|---|---|---|---|---|---|---|
| | Avg. (1) | Acct. (2) | AWAS (3) | NALIGALI (4) | PDS (5) | Pension (6) | Solar Light (7) |
| | *Panel A: Above and Below High-School* | | | | | | |
| Winner | 0.175** | 0.167 | 0.144 | 0.155 | 0.118 | 0.078 | 0.180 |
| | (0.079) | (0.121) | (0.111) | (0.126) | (0.208) | (0.220) | (0.122) |
| Bandwidth | 0.18 | 0.18 | 0.21 | 0.20 | 0.16 | 0.15 | 0.20 |
| Control Mean | 2.22 | 2.86 | 1.86 | 1.71 | 2.78 | 3.28 | 1.82 |
| Observations | 1,829 | 1,875 | 2,034 | 1,788 | 669 | 640 | 1,800 |
| | *Panel B: Above and Below Graduate* | | | | | | |
| Winner | 0.192* | 0.174 | 0.312** | -0.041 | 0.270 | 0.129 | 0.199 |
| | (0.101) | (0.146) | (0.149) | (0.182) | (0.250) | (0.276) | (0.155) |
| Bandwidth | 0.16 | 0.19 | 0.16 | 0.14 | 0.16 | 0.15 | 0.18 |
| Control Mean | 2.30 | 2.99 | 1.90 | 1.81 | 2.85 | 3.45 | 1.86 |
| Observations | 1,581 | 1,745 | 1,600 | 1,273 | 603 | 570 | 1,535 |

This table reports the effects of electing a more educated Mukhiya—defined as having above- primary education—on politician's scheme Knowledge. Estimates are obtained from a close-election regression discontinuity design using the 2016 Panchayat elections. Panel A reports results for electing a leader with above–high-school education, while Panel B reports results for electing a leader with above-graduate education.The outcome variable in column (1) is the average score created using knowledge of the six categories shown in column (2)-(7). All dependent variables are standardized across GPs. Robust standard errors are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A16: Effects of Political Competence on Network

| | Network (Contact Info.) | | | | Party | |
|---|---|---|---|---|---|---|
| | Mukhiya (1) | Panchayat Secretary (2) | BPRO (3) | BDO (4) | Party Involvement (5) | Political Support (6) |
| | *Panel A: Above and Below High-School* | | | | | |
| Winner | 0.008 | 0.108** | 0.144** | 0.171** | 0.013 | -0.002 |
| | (0.025) | (0.043) | (0.058) | (0.068) | (0.047) | (0.019) |
| Bandwidth | 0.16 | 0.21 | 0.18 | 0.15 | 0.21 | 0.18 |
| Control Mean | 0.94 | 0.81 | 0.35 | 0.42 | 0.21 | 0.03 |
| Observations | 1,734 | 2,039 | 1,849 | 1,649 | 2,044 | 1,838 |
| | *Panel B: Above and Below Graduate* | | | | | |
| Winner | -0.001 | 0.170*** | 0.206** | 0.136** | 0.096 | 0.048 |
| | (0.030) | (0.052) | (0.084) | (0.068) | (0.063) | (0.029) |
| Bandwidth | 0.15 | 0.15 | 0.13 | 0.20 | 0.18 | 0.17 |
| Control Mean | 0.95 | 0.83 | 0.37 | 0.44 | 0.21 | 0.03 |
| Observations | 1,484 | 1,449 | 1,359 | 1,816 | 1,721 | 1,644 |

This table reports the effects of electing a more educated Ward members—defined as having above- primary education—on politician's scheme Knowledge. Estimates are obtained from a close-election regression discontinuity design using the 2016 Panchayat elections. Panel A reports results for electing a leader with above–high-school education, while Panel B reports results for electing a leader with above-graduate education. Columns (1)–(4) examine political network outcomes, measured by whether the respondent knows the phone number of the Mukhiya (1), Panchayat Secretary (2), Block Panchayat Raj Officer (BPRO) (3), and Block Development Officer (BDO) (4). Columns (5)–(6) examine Ward members' party connections, measured by indicators for any party involvement (5) and receipt of political support (6). Robust standard errors are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A17: Alignment of Public Spending with Citizen Preferences

| | Overall | | SC Pref. | | Non-SC Pref. | |
|---|---|---|---|---|---|---|
| | Spending | Projects | Spending | Projects | Spending | Projects |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Above and Below High-School* | | | | | | |
| Above High-School | 22229.434 | 0.039 | 36272.647 | 0.201 | 6092.960 | 0.008 |
| | (38554.704) | (0.133) | (59733.556) | (0.237) | (40969.687) | (0.135) |
| Pref. | 2777468.559$^{***}$ | 6.586$^{***}$ | 1919622.903$^{***}$ | 5.230$^{***}$ | 2434939.874$^{***}$ | 5.729$^{***}$ |
| | (184776.156) | (0.445) | (186924.233) | (0.551) | (186258.330) | (0.421) |
| Above High-School × Pref. | 502805.276$^{*}$ | 1.205$^{*}$ | -160697.658 | -0.381 | 604732.388$^{**}$ | 1.587$^{**}$ |
| | (292014.105) | (0.665) | (286673.425) | (0.740) | (291916.886) | (0.673) |
| Dep. Mean | 463296.39 | 1.27 | 483295.63 | 1.35 | 462680.50 | 1.27 |
| Bandwidth | 0.13 | 0.20 | 0.13 | 0.20 | 0.13 | 0.20 |
| Observations | 5,715 | 7,500 | 3,105 | 3,885 | 5,580 | 7,350 |
| *Panel B: Above and Below Graduate* | | | | | | |
| Above Graduate | -10600.803 | -0.076 | 9566.461 | 0.060 | -22857.532 | -0.082 |
| | (47293.082) | (0.181) | (73776.396) | (0.352) | (47535.600) | (0.179) |
| Pref. | 2671999.883$^{***}$ | 5.936$^{***}$ | 1771972.918$^{***}$ | 3.847$^{***}$ | 2404363.629$^{***}$ | 5.327$^{***}$ |
| | (238370.008) | (0.526) | (219298.312) | (0.461) | (243664.441) | (0.528) |
| Above Graduate × Pref. | 240642.568 | 1.086 | -14210.429 | 1.196 | 293036.717 | 1.134 |
| | (332573.582) | (0.762) | (321151.296) | (0.797) | (331312.018) | (0.744) |
| Dep. Mean | 451632.07 | 1.21 | 466443.99 | 1.20 | 448337.54 | 1.19 |
| Bandwidth | 0.13 | 0.16 | 0.13 | 0.16 | 0.13 | 0.16 |
| Observations | 3,285 | 4,065 | 1,605 | 1,905 | 3,210 | 3,990 |

This table reports robustness checks for the heterogeneous effects of electing a more educated Mukhiya on government scheme outcomes by local citizen preferences, using alternative education thresholds. Panel (a) defines the more-educated candidate as having above-high-school education, while Panel (b) uses above-graduate education as the cutoff. All other specifications follow the main analysis: estimates are obtained from a close-election regression discontinuity design, controlling for scheme-specific measures of citizen preferences and their interactions with the treatment indicator. The outcome variables are scheme-level expenditures (*Spending*) and the number of projects implemented (*Projects*). Columns (1)–(2) use preferences of the overall population, Columns (3)–(4) use preferences of the Scheduled Caste population, and Columns (5)–(6) use preferences of the non–Scheduled Caste population. All specifications include scheme fixed effects. Standard errors are clustered at the running-variable level and reported in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# E Matching

As described in Section **??**, we match candidates to citizens in the SECC using a string-matching algorithm based on name, father/husband name, caste category, and gender. We restrict to matches with a similarity score of at least 0.95 and achieve an overall match rate of 60.2% for unreserved GP head candidates. Here we provide further details on the matching procedure and robustness to alternative thresholds.

The match rates are lower at the ward level because we do not have citizens' ward information (only GP). Our match rates are also lower for 2021 than 2016 because the SECC is more outdated for the former than the latter. Finally, our match rates are lower for women than men because marriage norms in India make women more mobile, since they leave their villages to be with their husbands. Thus, women who would have married into their husband's GP after the SECC was conducted will be missing from our data. Moreover, for women, the candidate data has either one of the father or husband's name and doesn't specify which one is mentioned, whereas for men the candidate data has only the father's name. The latter makes it more straightforward to match.

On balance, the candidates we find in the SECC look slightly different from the sample of candidates we do not match. In particular, our matched candidates are always somewhat older than our unmatched candidates. Our 2021 matched sample candidates are even older: the average matched candidate is abut 2.5 - 4.5 years older than average unmatched candidate. The corresponding range for 2016 candidates is 0.24 - 2 years. Education-wise, for the 2016 sample of candidates, there is no clear pattern: male GP head matched and unmatched candidates have similar education levels; female matched candidates (at both ward and GP head levels) have marginally lower education levels than their unmatched counterparts, while matched ward male candidates have slightly higher years of education. Caste-wise, we find more SC candidates in the SECC in 2021, but the patterns are more mixed for 2016 candidates.

Table A18: Balance Test of SECC and Electoral Candidates Data Matching

| | Education | | | | Caste | | | |
|---|---|---|---|---|---|---|---|---|
| | Yrs of Schooling | At least Literate | At least Secondary | At least Higher | SC | ST | Other | Age |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Panel A: Candidates Matching (55.36% candidates matched)* | | | | | | | | |
| Matched | -0.021 | 0.011*** | 0.003** | -0.012*** | 0.044*** | -0.019*** | -0.025*** | 2.604*** |
| | (0.015) | (0.001) | (0.002) | (0.001) | (0.001) | (0.000) | (0.001) | (0.025) |
| Control Mean | 5.465 | 0.899 | 0.376 | 0.137 | 0.250 | 0.010 | 0.740 | 41.627 |
| Observations | 361,293 | 363,217 | 363,217 | 363,217 | 908,511 | 908,511 | 908,511 | 907,560 |
| *Panel B: Candidates Fathers Matching (41.14% candidates matched)* | | | | | | | | |
| Father Matched | 1.128*** | 0.026*** | 0.101*** | 0.095*** | -0.055*** | -0.015*** | 0.070*** | -8.522*** |
| | (0.021) | (0.001) | (0.002) | (0.002) | (0.001) | (0.000) | (0.001) | (0.035) |
| Control Mean | 7.578 | 0.969 | 0.579 | 0.274 | 0.202 | 0.013 | 0.785 | 36.683 |
| Observations | 175,681 | 176,614 | 176,614 | 176,614 | 433,003 | 433,003 | 433,003 | 432,551 |

This table compares demographic characteristics of candidates who can be matched to the SECC data with those who cannot, using data from Mukhiya and Ward Panchayat elections in 2016 and 2021. Panel A presents balance tests for candidates, while Panel B presents balance tests for candidates' fathers. Columns (1)–(4) report education outcomes; Columns (5)–(7) indicate whether the candidate belongs to the Scheduled Caste, Scheduled Tribe, or general category; and Column (8) reports age, winsorized at the top and bottom 1 percent. Standard errors are clustered at the Gram Panchayat level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A19: Balance in observables between matched and non-matched candidates

| | Education | | | | Caste | | | |
|---|---|---|---|---|---|---|---|---|
| | Yrs of Schooling (1) | At least Literate (2) | At least Secondary (3) | At least Higher (4) | SC (5) | ST (6) | Other (7) | Age (8) |
| *Panel A: Mukhiya Man 2016 (63.62% candidates matched)* | | | | | | | | |
| Matched | 0.056 | 0.000 | 0.012** | -0.004 | -0.010*** | -0.006*** | 0.016*** | 0.927*** |
| | (0.048) | (0.002) | (0.005) | (0.005) | (0.003) | (0.001) | (0.003) | (0.120) |
| Control Mean | 8.495 | 0.973 | 0.660 | 0.342 | 0.248 | 0.031 | 0.721 | 42.643 |
| Observations | 46,843 | 47,178 | 47,178 | 47,178 | 47,178 | 47,178 | 47,178 | 47,130 |
| *Panel B: Mukhiya Woman 2016 (54.26% candidates matched)* | | | | | | | | |
| Matched | -0.853*** | -0.008*** | -0.072*** | -0.076*** | 0.005** | -0.004*** | -0.001 | 2.046*** |
| | (0.044) | (0.002) | (0.005) | (0.004) | (0.003) | (0.001) | (0.003) | (0.116) |
| Control Mean | 6.035 | 0.943 | 0.410 | 0.182 | 0.206 | 0.016 | 0.778 | 38.017 |
| Observations | 45,840 | 46,132 | 46,132 | 46,132 | 46,132 | 46,132 | 46,132 | 46,107 |
| *Panel C: Ward Man 2016 (63.83% candidates matched)* | | | | | | | | |
| Matched | 0.372*** | 0.018*** | 0.047*** | 0.009*** | 0.008** | -0.017*** | 0.009** | 0.240*** |
| | (0.031) | (0.001) | (0.003) | (0.002) | (0.004) | (0.001) | (0.004) | (0.049) |
| Control Mean | 5.838 | 0.930 | 0.409 | 0.154 | 0.234 | 0.030 | 0.736 | 41.331 |
| Observations | 128,845 | 129,447 | 129,447 | 129,447 | 129,447 | 129,447 | 129,447 | 129,065 |
| *Panel D: Ward Woman 2016 (57.83% candidates matched)* | | | | | | | | |
| Matched | -0.177*** | 0.010*** | -0.015*** | -0.019*** | 0.083*** | -0.017*** | -0.066*** | 0.537*** |
| | (0.023) | (0.003) | (0.003) | (0.001) | (0.005) | (0.001) | (0.004) | (0.048) |
| Control Mean | 3.665 | 0.795 | 0.196 | 0.054 | 0.194 | 0.024 | 0.783 | 38.968 |
| Observations | 138,446 | 139,144 | 139,144 | 139,144 | 139,144 | 139,144 | 139,144 | 138,704 |

Focusing on the GP and ward elections of 2016, this table shows how characteristics of those politicians we match in the SECC data vary from those we do not find. Age is winsorized at top and bottom 1 percentile. Panel (A-B) and (C-D) respectively include GP and Ward level fixed effects. Standard errors are clustered at the same level as the fixed effects.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Balance in observables between matched and non-matched candidates

| | Caste | | | |
|---|---|---|---|---|
| | SC | ST | Other | Age |
| | (1) | (2) | (3) | (4) |
| *Panel A: Mukhiya Man 2021 (53.14% candidates matched)* | | | | |
| Matched | 0.012*** | -0.013*** | 0.002 | 4.478*** |
| | (0.003) | (0.001) | (0.003) | (0.153) |
| Control Mean | 0.173 | 0.030 | 0.797 | 42.268 |
| Observations | 30,654 | 30,654 | 30,654 | 30,654 |
| *Panel B: Mukhiya Woman 2021 (48.7% candidates matched)* | | | | |
| Matched | 0.011*** | -0.010*** | -0.001 | 3.820*** |
| | (0.003) | (0.001) | (0.003) | (0.146) |
| Control Mean | 0.140 | 0.017 | 0.843 | 38.930 |
| Observations | 31,242 | 31,242 | 31,242 | 31,241 |
| *Panel C: Ward Man 2021 (51.86% candidates matched)* | | | | |
| Matched | 0.051*** | -0.018*** | -0.033*** | 4.125*** |
| | (0.004) | (0.001) | (0.004) | (0.056) |
| Control Mean | 0.191 | 0.032 | 0.777 | 38.865 |
| Observations | 225,601 | 225,601 | 225,601 | 225,578 |
| *Panel D: Ward Woman 2021 (52.3% candidates matched)* | | | | |
| Matched | 0.084*** | -0.023*** | -0.061*** | 2.501*** |
| | (0.003) | (0.001) | (0.003) | (0.066) |
| Control Mean | 0.164 | 0.029 | 0.806 | 38.507 |
| Observations | 256,392 | 256,392 | 256,392 | 256,359 |

Focusing on the GP and ward elections of 2021, this table shows how characteristics of those politicians we match in the SECC data vary from those we do not find. Age is winsorized at top and bottom 1 percentile. Panel (A-B) and (C-D) respectively include GP and Ward level fixed effects. Standard errors are clustered at the same level as the fixed effects.$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A21: Balance in observables between matched and non-matched candidates fathers

| | Education | | | | Caste | | | |
|---|---|---|---|---|---|---|---|---|
| | Yrs of Schooling | At least Literate | At least Secondary | At least Higher | SC | ST | Other | Age |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Panel A: 2016 Mukhiya (36.52% candidates fathers matched)* | | | | | | | | |
| Father Matched | 0.889*** | 0.007*** | 0.073*** | 0.096*** | -0.022*** | -0.004*** | 0.026*** | -8.538*** |
| | (0.043) | (0.001) | (0.004) | (0.005) | (0.002) | (0.001) | (0.002) | (0.107) |
| Control Mean | 9.339 | 0.980 | 0.736 | 0.419 | 0.223 | 0.013 | 0.764 | 37.987 |
| Observations | 46,843 | 47,178 | 47,178 | 47,178 | 47,178 | 47,178 | 47,178 | 47,130 |
| *Panel B: 2016 Ward (37.7% candidates fathers matched)* | | | | | | | | |
| Father Matched | 1.421*** | 0.039*** | 0.137*** | 0.102*** | -0.049*** | -0.011*** | 0.060*** | -9.128*** |
| | (0.024) | (0.001) | (0.003) | (0.002) | (0.002) | (0.001) | (0.002) | (0.062) |
| Control Mean | 6.958 | 0.965 | 0.524 | 0.222 | 0.208 | 0.013 | 0.779 | 35.823 |
| Observations | 128,845 | 129,447 | 129,447 | 129,447 | 129,447 | 129,447 | 129,447 | 129,065 |

Focusing on the GP and ward elections of 2016, this table shows how characteristics of those politicians whose fathers we match in the SECC data vary from those whose fathers we do not find. Age is winsorized at top and bottom 1 percentile. Panel (A-B) and (C-D) respectively include GP and Ward level fixed effects. Standard errors are clustered at the same level as the fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A22: Balance in observables between matched and non-matched candidates fathers

| | Caste | | | |
|---|---|---|---|---|
| | SC | ST | Other | Age |
| | (1) | (2) | (3) | (4) |
| *Panel A: 2021 Mukhiya (41.61% candidates fathers matched)* | | | | |
| Matched | -0.015*** | -0.009*** | 0.024*** | -7.750*** |
| | (0.003) | (0.001) | (0.003) | (0.138) |
| Control Mean | 0.172 | 0.015 | 0.813 | 40.105 |
| Observations | 30,654 | 30,654 | 30,654 | 30,654 |
| *Panel B: 2021 Ward (43.78% candidates fathers matched)* | | | | |
| Matched | -0.031*** | -0.019*** | 0.051*** | -8.136*** |
| | (0.002) | (0.001) | (0.002) | (0.048) |
| Control Mean | 0.200 | 0.012 | 0.788 | 36.438 |
| Observations | 225,601 | 225,601 | 225,601 | 225,578 |

Focusing on the GP and ward elections of 2021, this table shows how characteristics of those politicians whose fathers we match in the SECC data vary from those whose fathers we do not find. Age is winsorized at top and bottom 1 percentile. Panel A and B respectively include GP and Ward level fixed effects. Standard errors are clustered at the same level as the fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# F Seat reservation rule

Bihar has reservations for SCs, STs, EBCs (*not* OBCs) and women. The rule for these is given below. The crucial takeaway from the sections below is that, within each caste-reserved and caste-unreserved GPs, there exists a population threshold above which all seats are gender-reserved. Note, also, that the rule for 2006 is fixed till 2016 (two election cycles), after which the reservation cycle switches Below, we describe the reservation algorithm for caste/gender for 2016 and 2021 (the relevant period in our study).

## F.1 Caste Reservation

- First, based on the proportion of SCs (STs) in the block, the number of GPs to be reserved for SCs (STs) is decided. If there are $N_j$ GPs in block $j$ and $\theta_j$ is the proportion of SCs (STs) in block $j$, then the number of GPs, $n_j$, to be reserved is

$$n_j = round(\theta_j * N_j, 1)$$

- Let $n_{SC}$ and $n_{ST}$ be the number of GPs to be reserved in block $j$ for SCs and STs, respectively. The number of GPs to be reserved for EBCs is given by

$$n_{EBC} = min(round(0.2 * N_j, 1), round(0.5 * N_j - n_{SC} - n_{ST}, 1))$$

- Now, all GPs are rearranged in the descending order of their non SCST population. The first GP on this truncated list is "blocked". The choice of word is deliberate and conveys an important distinction: the GP is not "reserved", it is merely blocked.
- Now, all unreserved and unblocked GPs are rearranged in descending order of their SC population. The first GP in this further truncated list is now reserved for SCs, unless it has already been reserved for SCs in the 2006-16 reservation cycle. If the latter, then the next GP in the list is selected.
- If there are no STs in the block or $n_{ST}$ is 0 (which is true in 480 of the 534 blocks), then the rule skips to the next step. However, if $n_{ST} > 0$, the rule proceeds by arranging all remaining GPs in descending order of their ST population. The first GP in the list is then reserved for STs (unless it has already been reserved for STs in the previous cycle, in which case, the 2nd GP in the list is picked).
- This algorithm proceeds until the number of GPs reserved for STs = $n_{ST}$ or the number reserved for SCs is $n_{SC}$. Once, a group hits its quota of reserved GPs, then the rearranging of GPs is no longer done by that group. For instance, if $n_{ST} = 1$, then, in the second round, GPs are no longer rearranged by ST population - instead, the rule proceeds straight to rearranging by non-SCST population.
- The algorithm further proceeds till the second group also hits its quota of reserved GPs. This throws up two sets of GPs, $n_{ST}$ GPs that are reserved for STs and $n_{SC}$ GPs that are reserved for SCs.

- Now, all the unreserved GPs (including the "blocked" ones) are collected and arranged by descending order of GP population.
- The first $n_{EBC}$ GPs in this list is reserved for EBCs.
- Thus, for each block, one can arrive at an SC population cut-off - the SC population of the last GP to be reserved for SCs - below which no GP is reserved. This threshold varies by block. Figure **??** gives the first stage and shows that the first stage is robust to (a) adding block fixed effects (Panel (b)) and (b) dropping all ST/EBC reserved GPs.

### F.2 Gender Reservation

- All the $n_{SC}$ seats determined to be reserved for SCs within a block are arranged in descending order of SC population and *up to* 50% of them with the highest populations are reserved for SC women. For instance, if there are $n_{SC} = 3$, then 1 GP is reserved for SC women – the one with the highest SC population. On the other hand, if $n_{SC} = 4$, then 2 GPs are reserved for SC women – the top 2 highest SC population GPs.
- All the $n_{ST}$ seats determined to be reserved for STs within a block are arranged in descending order of ST population and *up to* 50% of them with the highest ST populations are reserved for ST women.
- All the $n_{EBC}$ seats determined to be reserved for EBCs within a block are arranged in descending order of total population and *up to* 50% of them with the highest total populations are reserved for EBC women.
- All the $n_{GEN}$ seats determined to be caste unreserved within a block are arranged in descending order of non-SCST population and *up to* 50% of them with the highest non-SCST populations are reserved for women.

# G Consequences of Gender Reservation

In this section, we study the consequences of gender reservation on two schemes studied previously in the paper: the implementation of the NREGA and WAS projects. We use the same fuzzy RD strategy described previously to uncover causal effects of gender reservation.

Tables A23 and Table A24 below show the results. Reservation largely has no effects on either set of outcomes. There are marginally fewer WAS projects in reserverd GPs (5% fewer), but amount spent on projects does not change. Moreover, effects do not vary when broken down by caste.

Table A23: Effects of reservation on development outcomes

| | NREGA Work-Day | | | | | Village Projects | |
|---|---|---|---|---|---|---|---|
| | Total Work-Day (1) | Women Work-Day (2) | Men Work-Day (3) | SC Work-Day (4) | Non-SC Work-Day (5) | Total Projects (6) | Total Amounts (7) |
| *Panel A: Comparison to All Mukhiya Winners* | | | | | | | |
| Female RSVN | -247.327 | -269.372 | 46.962 | -20.010 | -218.183 | -1.263** | 9081.357 |
| | (407.436) | (234.670) | (208.658) | (123.888) | (334.424) | (0.609) | (443534.654) |
| Bandwidth | 863.72 | 854.82 | 856.14 | 841.08 | 884.65 | 961.15 | 1011.50 |
| Control Mean | 15679.488 | 8261.084 | 7486.388 | 2868.709 | 12823.346 | 20.166 | 9460208.883 |
| Observations | 3,780 | 3,770 | 3,772 | 3,740 | 3,820 | 3,688 | 3,755 |
| *Panel B: Comparison to Female Mukhiya Winners* | | | | | | | |
| Female RSVN | -529.502 | -321.890 | -109.569 | 71.894 | -591.450 | 0.124 | 879324.320 |
| | (451.169) | (242.046) | (240.258) | (147.207) | (375.743) | (0.764) | (570562.398) |
| Bandwidth | 1120.21 | 1162.04 | 1064.05 | 1025.67 | 1112.22 | 1063.87 | 984.43 |
| Control Mean | 15781.004 | 8267.845 | 7547.391 | 2841.388 | 12945.996 | 20.628 | 9688757.034 |
| Observations | 2,763 | 2,801 | 2,721 | 2,694 | 2,755 | 2,548 | 2,493 |

This table shows the effects of female reservation on development outcomes. Only 2016 candidates are included in the sample. Panel (A) compares the development outcomes of reserved GPs with unreserved GPs, while Panel (B) restrict the comparison to female winners only. The running variable 'Population Diff.' represents the difference between the Gram Panchayat population and the cutoff population size (the population cutoff line is calculated by taking the average population size between the last reserved Gram Panchayat and the first unreserved Gram Panchayat). Controls include fixed effects on election year. Standard errors are clustered at Block level and shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A24: Effects of Reservation on Development Outcomes

| | NREGA Work-Day | | | | | Village Projects | |
|---|---|---|---|---|---|---|---|
| | Total Work-Day | Women Work-Day | Men Work-Day | SC Work-Day | Non-SC Work-Day | Total Projects | Total Amounts |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | | | | *Panel A: Unreserved* | | | |
| Female RSVN | -943.435 | -547.817 | -326.251 | -496.796 | -453.359 | -1.305 | -458969.678 |
| | (932.549) | (523.220) | (472.285) | (303.266) | (772.014) | (1.840) | (886410.549) |
| Bandwidth | 2032.27 | 2239.09 | 1918.80 | 1888.33 | 2086.56 | 2084.47 | 2077.52 |
| Observations | 2,472 | 2,585 | 2,420 | 2,407 | 2,503 | 2,334 | 2,329 |
| | | | | *Panel B: SC Reserved* | | | |
| Female RSVN | 599.964 | -30.915 | 471.947 | 302.222 | 349.957 | 0.291 | 869103.828 |
| | (1209.123) | (735.848) | (647.907) | (369.598) | (1049.438) | (2.860) | (1304813.433) |
| Bandwidth | 314.17 | 313.13 | 302.15 | 344.61 | 303.02 | 355.09 | 354.22 |
| Observations | 909 | 907 | 890 | 941 | 891 | 888 | 888 |
| | | | | *Panel C: ST Reserved* | | | |
| Female RSVN | -13983.980 | -6283.692 | -7629.966 | -2801.279 | -11143.168 | 29.101 | 6041102.486 |
| | (9338.292) | (5125.870) | (5162.168) | (2000.369) | (8004.875) | (21.463) | (9830281.099) |
| Bandwidth | 174.65 | 167.38 | 177.41 | 177.45 | 168.47 | 206.66 | 208.86 |
| Observations | 21 | 21 | 21 | 21 | 21 | 19 | 19 |
| | | | | *Panel D: OBC Reserved* | | | |
| Female RSVN | -1384.040 | -464.378 | -735.557 | -151.409 | -1102.255 | -3.176 | 1350225.934 |
| | (1742.608) | (988.146) | (894.908) | (450.857) | (1551.996) | (3.373) | (2770700.845) |
| Bandwidth | 512.77 | 525.59 | 496.82 | 750.74 | 507.27 | 536.98 | 584.58 |
| Observations | 761 | 773 | 742 | 927 | 754 | 726 | 771 |

This table shows the effects of female reservation on NREGA and village project development outcomes. Only 2016 candidates are included in the sample. Panel (A)-(D) shows the regression results broken down by caste reservation status. The running variable 'Population Diff.' represents the difference between the Gram Panchayat population and the cutoff population size (the population cutoff line is calculated by taking the average population size between the last reserved Gram Panchayat and the first unreserved Gram Panchayat). Controls include fixed effects on election year. Standard errors are clustered at Block level and shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# H Close-Election Regression Discontinuity Design on Politician Knowledge and Network

This appendix describes the close-election regression discontinuity (RD) design used to identify the effects of education on politician knowledge and networks. To support the use of education as a proxy for competence, we examine whether more educated leaders have greater knowledge of scheme implementation as well as broader political networks and stronger party connections. The questions on knowledge and networks were part of the baseline survey data of 7719 WMs, taken from (Bamezai et al., 2024).

We implement an RD design that exploits close electoral races in 2021 ward-level elections.

Following a similar strategy in Section **??** and Section **??**, we restrict our sample to ward-level elections where the top two finishers differ in their attainment of primary education. We estimate:

$$Y_w = \mu + \theta \mathbb{1}\{MoV_w > 0\} + \gamma_1 MoV_g + \gamma_2(\mathbb{1}\{MoV_w > 0\} \times MoV_w) + \varepsilon_w, \qquad (10)$$

where $Y_w$ denotes the outcome variable of winning candidate in ward $w$. The running variable, $MoV_w$, is the vote share margin between the candidate with above-primary education and the candidate with primary education or below. Treatment indicator equals 1 if the more educated candidate wins ($MoV_w > 0$). The coefficient $\theta$ identifies the local average treatment effect of electing a more educated ward member. We also control for if candidates are running for themselves or a family members. Standard errors are clustered at ward-level.

We evaluate the impact of politician's education level on two sets of outcomes. First, we measure institutional and scheme knowledge by assessing whether candidates can correctly identify the administrative steps required to implement various government programs. This includes the setup of ward member accounts, the implementation of solar street lights, and the procedural requirements for giving out social pensions, the Public Distribution System, drains and lanes, and housing schemes. Table A3 documents the results. More educated WMs are able to name 18% more steps than control WMs (Column 1), driven by greater knowledge of housing, solar lights and ward accounts.

Second, we look at for the politicians' political network. This is measured by an indicator for whether the ward member possesses the direct contact information for key block and panchayat officials—specifically the Block Development Officer (BDO), the Block Panchayat Raj Officer (BPRO), the GP head, and the Panchayat Secretary. Additionally, we also capture partisan support through the member's formal involvement with political parties and whether they received external political support during their campaign. Table A4 shows that WMs have wider networks, especially with the key bureaucrats: the GP Secretary and the Block Development Officer. Moreover, they are also more likely to be linked to political parties.

Lastly, our results are robust to the alternative choice of educational threshold. Tables A15 and A16 show that the estimated effects persist when defining the treatment based on high school completion or university graduation. These results suggest that the benefits of candidate education are not idiosyncratic to the primary school margin.

# I Citizen Survey and Conjoint Experiment Design and Implementation Details

This appendix provides additional details on the primary survey used to elicit citizen preferences over candidate characteristics, including education, through a conjoint experiment. This citizen survey was conducted as part of Bamezai (2025; FIXME) under the University of Pennsylvania (IRB Protocol #855284). The study was pre-registered on the Open Science Framework (Registry ID: p65hr). Details are available at https://osf.io/p65hr.

## I.1 Survey Implementation and Sample Composition

The survey was fielded between February and March 2024 across 48 Gram Panchayats (GPs) located in two districts of Bihar. The study yielded a total of 1,105 completed interviews, comprising 969 citizens, 110 elected Ward Members (WMs), 3 GP heads, and 23 frontline workers (including Anganwadi workers, ASHAs, and other local functionaries). All respondents were included in the conjoint analysis.

## I.2 Sampling Strategy

The sampling strategy was designed to capture heterogeneity in political experiences and expectations at a highly local level. GPs in Bihar typically comprise multiple revenue villages and wards, with substantial variation across caste, religion, and socio-economic status. Given this heterogeneity, sampling was conducted at the ward level.

Two districts were selected: Bhojpur and Samastipur. Within each district, three blocks were randomly selected. From each block, eight GPs were randomly sampled, and within each Panchayat, four wards were selected, yielding a total of 192 wards.

Within each ward, enumerators were instructed to complete up to six interviews, subject to time and travel constraints. Households were selected using a standard random-walk procedure. Enumerators first obtained an estimate of the total number of households in the ward from either the elected ward member or a frontline worker, and then selected every $k$-th household, where $k$ equals the total number of households divided by six and rounded down. If a household refused consent or no eligible respondent was available, the enumerator moved to the next household.

Within selected households, one respondent aged 18–75 was randomly chosen using the survey instrument. Enumerators also interviewed the ward member or a frontline worker in the ward when consent was provided. Approximately 25% of interviews were conducted with female respondents. This share reflects feasibility constraints encountered during piloting, which indicated substantial difficulty among many women respondents – particularly those with lower education levels – in answering questions related to Panchayat elections and candidate evaluation.

## I.3 Conjoint Experiment Design

The conjoint experiment was embedded within the survey to elicit respondent preferences over hypothetical Panchayat candidates. Each respondent was shown paired profiles of two hypothetical individuals residing in a village similar to their own. Respondents were explicitly informed that the two profiles were identical in all respects except for the attributes shown, thereby holding representativeness constant.

Candidate profiles varied randomly across seven attributes, one of which was education. All seven attributes are described below:

### I.3.1 Conjoint experiment: Other attributes

1. **Education level**: There are three levels: (i) completed 5th grade, (ii) completed 10th grade, and (iii) completed B.A.. Each candidate can be assigned one of the three levels withequal probability (0.33 each).

2. **Gender**: There are two levels: male and female. Each candidate can be assigned one of the two values with equal probability (0.5 each).

3. **Caste category**: There are three levels here: (i) Scheduled caste category (like Paswan, Chamar, Manjhi, etc.), (ii) Backward caste category (like Yadav, Kurmi, etc.), (iii) General caste category (like Bhumihar, Rajput, etc.). Each candidate can be assigned one of the three levels with equal probability (0.33 each).

4. **Behavior/personality ("vyavhaar")**: There are two levels here: (i) very good, and (ii) not very good. Each candidate can be assigned one of the two levels with equal probability (0.5 each).

5. **Previous family experience in local electoral politics**: There are two levels: (i) no such experience, and (ii) someone in the family has been in an elected Panchayat position before (like Mukhiya, Sarpanch, etc.). Each candidate can be assigned one of the two levels with equal probability (0.5 each).

6. **Presence of a government worker in the family**: Therer are two levels: (i) yes, and (ii) no (0.5 each).

7. **Other source of family income**: There are four levels here: (i) Wage labor, (ii) Farming, (iii) Business, (iv) Private job. Each candidates can be assigned one of the four levels with equal probability(0.25 each). The decision to include this attribute was based on my learning that there are barely any households who rely entirely on a government job for their household's subsistence. In rural Bihar, many families will have at least one other source of household income.

For each profile pair, respondents were asked two questions: (a) which individual they believed was more likely to contest a Panchayat election; and (b) conditional on both contesting, which individual was more likely to win the election.

Respondents completed three conjoint tasks if their own education was below 10th grade, and four tasks if they had completed 10th grade or higher. This design yielded approximately 7,600 evaluated profile pairs.