The Limits of Political Representation: Evidence from India

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Abstract

Political inclusion is widely believed to improve governance, which has motivated the creation of elected representatives for highly localized constituencies. This paper studies 1.2 million "hyperlocal" representatives across 150,000 local governments in rural India. Exploiting discontinuities that determine the number and identity of these representatives, we assess how expanded representation affects governance outcomes. We find precisely estimated null effects on core functions, including public project management, intermediation in access to welfare programs, oversight of public finances, and the equity of benefit allocation. These findings highlight the limits of expanding political representation if representative capacity is weak.

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1 Introduction

Developing countries have increasingly embraced decentralization reforms. A central premise of these initiatives is that expanding local political representation can improve the delivery of public goods by narrowing information and accountability gaps between constituents and decision-makers. This logic has motivated the introduction of a class of elected representatives for highly localized constituencies that may encompass as few as a hundred people. These "hyperlocal" representatives appear to constitute the world's largest class of elected officials by population, with at least five million currently active across many countries. Yet despite their prevalence, there is little causal evidence on how expanding representation at this margin affects governance outcomes.

Classic theories predict that expanding political representation should improve governance. More localized representatives may better understand or align with constituent preferences (Tiebout, 1956; Oates et al., 1972), face stronger accountability through social and electoral sanctions (Seabright, 1996; Boffa et al., 2016), or be more accessible to citizens in facilitating access to government-provided benefits (Bussell, 2019). Increased proximity between voters and political representatives may particularly benefit marginalized communities that would otherwise be politically excluded. Whether these mechanisms translate into improved governance in practice, however, depends on how representatives are positioned within institutions. If representatives extract corrupt rents, act as additional veto players that stall decision-making (Tsebelis, 2002), or lack the capacity or policy knowledge to influence outcomes (Auerbach et al., 2023), expanded representation may fail to deliver the anticipated benefits.

This paper studies the largest group of hyperlocal representatives globally: ward members in India's village councils (gram panchayats, or GPs). GPs oversee the provision of local public goods, assist in a range of national welfare schemes, and implement a major workfare program, among other functions. Each GP includes a single elected head and multiple ward members, who are elected from geographically distinct wards within the GP. There are over 2.6 million ward members across India, and they typically serve constituencies ranging from one hundred to one thousand residents. Their functions are comparable to those of hyperlocal representatives in other settings, such as Badan Perwakilan Desa in Indonesia (Antlöv et al., 2016) or village committees in China (Shi, 1999). Our analysis examines three core tasks of hyperlocal representatives (Ministry of Rural Development, 2020a): (1) supporting the implementation of local government projects; (2) providing intermediation services to constituents; and (3) exercising oversight over public projects and finances.

We assemble a novel dataset of over 1.2 million ward members across 150,000 gram pan-

chayats in 13 Indian states, collectively representing nearly 600 million constituents. We investigate two margins of representation — "density" (the ratio of representatives to residents) and the identity of representatives. To study the impact of representative density, we take advantage of state-specific thresholds that govern the number of hyperlocal representatives within a local government unit. At certain population thresholds, this number increases, creating discontinuities in representative "density". For example, in the state of Tamil Nadu, a GP with just under 2,000 residents has six ward members, while one just above has nine—a 50% increase in density. We use these thresholds in a regression discontinuity design to estimate the effects of increased representation.

Expanding representation often broadens the composition of those serving in political office. To explore the impact of the identity of hyperlocal representatives, we leverage a rule governing the caste composition of village councils, under which some ward member positions can only be contested by members of a marginalized group (Scheduled Castes, or SCs). The number of these "reserved" seats depends on the SC population share of the GP, with stepwise increases at specific thresholds. We use these thresholds in a regression discontinuity framework to estimate the causal effects of increased hyperlocal representation from marginalized communities.

We first examine how hyperlocal representatives affect the implementation and distribution of benefits from public projects, focusing on the National Rural Employment Guarantee Scheme (NREGS) workfare program. Representatives could influence outcomes by assisting implementing agents, pressuring them to improve performance, or lobbying on behalf of constituents. However, we find no evidence that either greater representative density or increased representation of marginalized groups improves any workfare outcomes, including access to job cards, days of employment, or project completion. Our estimates are highly precise, ruling out improvements as small as 0.017 standard deviations on an index of workfare outcomes. Disaggregating outcomes by beneficiary caste yields similarly precise null effects across marginalized and non-marginalized groups. Using novel geocoded data on the location of tens of millions of NREGS projects, we also find no evidence of changes in the spatial distribution of projects.

Another key responsibility of hyperlocal representatives is to facilitate access to individual benefits. Many citizens of developing countries face barriers to claiming public entitlements due to illiteracy, administrative complexity, or limited political networks (Gupta, 2025), and local representatives may help bridge these access gaps. We measure intermediation success using village-level data on eight targeted welfare programs (e.g., ration cards, housing subsidies, pensions). Again, we find precisely estimated null effects on access to these programs under both empirical strategies.

Finally, we test whether hyperlocal representatives influence project management and corruption. Representatives may increase accountability by monitoring the work of other politicians or bureaucrats, but alternatively, could increase corruption by creating additional demands for corrupt rents. We test these channels using data from three years of financial audits of GP accounts and nine years of social audits of the NREGS workfare program. We find no effect of either representative density or identity on the incidence and composition of irregularities, with sufficient statistical power to rule out even modest effects. Our results suggest that hyperlocal representatives do not measurably shape corruption or oversight in this setting.

Our analysis estimates the effects of marginal increases in representative density and representation of marginalized groups. One interpretation of the findings is that hyperlocal representatives do not meaningfully affect major governance outcomes in this setting. Alternatively, the results could reflect features of our empirical strategy: for example, representation may exhibit diminishing returns, with our estimates dominated by ranges where additional representation has little effect. The final section of the paper conducts seven empirical tests to probe these and other explanations, such as directly testing for diminishing marginal returns and using data from over 1.2 million GP meetings to unpack local government deliberative processes. These tests conclude that our results are best explained by the first interpretation — that ward members fail to meaningfully shape key governance outcomes — despite having a small effect on citizen engagement in the political process.

Our paper contributes to the large literature emphasizing how political representation can improve governance by increasing responsiveness, accountability, and alignment with citizen preferences (e.g., Oates et al., 1972; Seabright, 1996; Besley, 2006; Besley and Coate, 2003; Ashworth, 2012). At the same time, it is unclear whether representation alone—absent direct control over budgets, personnel, or formal policy decisions—is sufficient to generate such improvements (e.g., Mansbridge, 1999; Bardhan and Mookherjee, 2006). Even without such authority, representatives may still matter by providing an institutionalized channel through which citizen grievances and preferences are voiced, legitimizing citizen claims in bureaucratic interactions, or serving as a focal point for oversight when citizens would otherwise have weak individual incentives to monitor service delivery (Besley and Burgess, 2002; Björkman and Svensson, 2009; Olken, 2007). Hyperlocal representatives provide a particularly clean setting to examine this question, as they maximize proximity to citizens while holding limited formal authority. Our findings shed light on the conditions under which political inclusion translates into effective governance, offering a cautionary tale particularly relevant for decentralization initiatives. The results indicate that simply expanding representation need not guarantee improvements in public service delivery without complementary investments in authority or

training.

We also contribute to the literature on how the institutional design of local government shapes service delivery in developing countries. A growing body of work studies how local political institutions—such as democratization (Olken, 2010; Martinez-Bravo et al., 2022), the delineation of political boundaries (e.g., Pierskalla, 2016; Narasimhan and Weaver, 2024; Dahis and Szerman, 2025), and the size of municipal legislatures (Freire et al., 2023; Britto and Fiorin, 2020)—affect government spending and public goods provision. Related research has particularly focused on the identity or incentives of heads of local governments, with much of this work examining affirmative action for these positions (e.g., Chattopadhyay and Duflo, 2004; Beaman et al., 2009, 2011; Martinez-Bravo, 2014; Sharan and Kumar, 2021). We complement this literature by shifting attention away from executive authorities to focus on a ubiquitous but understudied feature of local governance: hyperlocal representatives. Using expansive administrative data, we examine how hyperlocal representatives affect project implementation and the distribution of public goods, offering new evidence on determinants of local service delivery.

2 Background

Rural village councils, known as gram panchayats (GPs), have existed in India since pre-colonial times, but the 73^{rd} Amendment to the Constitution in 1992 established a uniform national framework for decentralization and village-level elections. Similar local governance reforms were introduced around the same time in other large developing countries, including Indonesia and China. A core feature of the 73^{rd} Amendment was the devolution of responsibilities to local governments across 29 areas, including education, sanitation, and drinking water. GPs also implement large-scale welfare programs, most notably the National Rural Employment Guarantee Scheme (NREGS) workfare program. Beyond these formal responsibilities, political science research highlights the informal influence of GP leaders in facilitating citizen access to government services, such as disseminating information and guiding applicants through bureaucratic processes (Chauchard, 2017; Bussell, 2019): for example, Kruks-Wisner (2018) finds that 62% of respondents seeking welfare assistance report turning to members of the village council.

The political leadership of a GP comprises a council head and ward members.[1] GPs are typically divided into five to twenty smaller geographical units (wards), with one elected ward member per ward. Wards are delimited to have approximately equal population,

[1]Terminology varies across states (e.g., "pradhan", "mukhiya," "sarpanch," or "president" for the head). For clarity, we use "head" and "ward member" throughout.

though their average size varies across states: in some states, wards may consist of only 100-200 people; in others, they may exceed 1,000 (see Table A1). The political leadership is supported by administrative staff such as a panchayat secretary, although staffing structure varies across states (Kerala Institute of Local Administration, 2023). In most states, both head and ward member positions are filled via simultaneous, nonpartisan, first-past-the-post elections held every five years. Although there are no formal term limits, India's political reservation system applies to both roles, restricting candidacy in some seats to women and/or Scheduled Castes (SC), Scheduled Tribes (ST), or Other Backward Classes (OBC).

One major constraint for research on hyperlocal representatives globally has been the lack of data on this level of government. As described in detail in Appendix B.1, we overcome this issue by combining five data sources to construct a data set of 2.07 million currently active ward members across 209,531 GPs, representing 78% of all GPs in India; approximately 1.2 million of these are in our 13 sample states.[2] Reflecting reservation policies, women constitute 50.8% of ward members. Caste composition is broad-based, with 24.6% general caste, 39.3% OBC, 23.4% SC, and 12.7% Scheduled Tribe. Ward members are typically middle-aged and have low levels of formal education: 41.2% are illiterate or have less than primary schooling, and only 2.2% hold a college degree or higher, raising concerns that education may constrain their capacity.

As described in training materials created by the Ministry of Rural Development, the role of ward members is to identify and address problems in their wards, ensure last-mile delivery of government schemes to their constituents, participate in local government decision-making and administration (e.g., creation of development plans), and oversee specific local government functions, particularly through membership on committees of the gram panchayat (e.g. school management committee) (Ministry of Rural Development, 2020a). As part of this, they should participate in meetings of the gram panchayat, which are supposed to have a quorum of ward members present and occur at least monthly. Ward members almost always have another form of employment since they are typically unpaid or receive only a small honorarium (Ministry of Panchayati Raj, 2022).

In practice, member efficacy is dependent on institutional factors. The head is generally seen as the most powerful figure in GP governance due to their control over finances (Ministry of Rural Development, 2020a). As training materials describe, ward members still may have a meaningful role by representing citizen interests with the head, assisting in implementation,

[2]The Uttar Pradesh and West Bengal State Election Commissions provide ward member names and demographic information for recent elections. The Mahaegram initiative supplies ward member rosters for Maharashtra. For the remaining states, we draw on two Ministry of Panchayati Raj databases: Gram Manchitra, which reports education, age, gender, and caste, and eGramSwaraj, which reports names and gender. Appendix B.1 discusses how we handle missing data in these data sets.

and monitoring GP activities, but their limited ability to impose formal sanctions may hamper their capabilities. However, aside from small-scale qualitative accounts (e.g., HCL Foundation, 2020; Harinath, 2024), there is little rigorous evidence on intra-council power dynamics and whether such hyperlocal representatives actually influence local governance.

3 Empirical Strategy

Our main analysis uses two regression discontinuity (RD) designs to study how hyperlocal representation affects public goods delivery. The first design focuses on representative density, measured as the ratio of ward members to constituents. In eight states, statutory rules increase the number of ward members at discrete population thresholds based on the gram panchayat population in the prior decennial census. These rules vary across states. For example, in Punjab, the number of ward members increases from 5 to 7 at a population of 1,000 and from 7 to 9 at a population of 2,000, while in Andhra Pradesh it increases from 9 to 11 at a population of 1,500 and from 11 to 13 at a population of 3,000 (see Table A1 for all the rules).

Typically established under state Panchayati Raj Acts in the 1990s, these rules generate sharp discontinuities in representative density, making them well suited to an RD design: GPs just above a threshold have discretely higher representative density than otherwise comparable GPs just below it. In these states, we estimate the following specification:

$$Y_{g,s,t} = \gamma_0 + \gamma_1 \mathbf{1}(p_{g,s} \geq 0) + \gamma_2 f_1(p_{g,s}) + \gamma_3 f_2(p_{g,s}) \cdot \mathbf{1}(p_{g,s} \geq 0) + \epsilon_{g,s} \tag{1}$$

Here, $Y_{g,s,t}$ is the outcome of interest in GP g in state s at time t. The running variable $p_{g,s}$ is defined as the difference between GP g's population in the relevant census year and the nearest population threshold determining ward member allocation (e.g., 1,000, 2,000, and higher thresholds in the example of Punjab).[3] The functions $f_1(p_{g,s})$ and $f_2(p_{g,s})$ allow for flexible functional forms on either side of the cutoff. We aggregate across multiple thresholds, so γ_1 represents a weighted average treatment effect across several discontinuities that we later disaggregate. Estimation follows Calonico et al. (2014), using a triangular kernel, local linear regression, and MSE-optimal bandwidths as in Calonico et al. (2018). In cases with multiple years of data for the same GP, we employ a stacked specification with standard errors clustered at the GP level.[4]

[3]For construction of the running variable, we match villages to GPs using the Local Government Directory (Ministry of the Panchayat Raj, 2020) and take village-level population data from the Census of India (Census of India, 2001, 2011).

[4]While the outcome data is from 2016 to 2025, the delimitation of wards typically occurs in the first election cycle after the 2011 census. Boundaries have remain relatively fixed since then due to the lack of

A key concern is whether these rules are implemented as written. Using roster data on ward members, we test this by estimating Equation 1 with the actual number of representatives as the outcome. Column (1) of Table 1 and Panel A of Figure 1 show a strong first stage: GPs just above the threshold have 1.4 more ward members than those below. Appendix Table A2 confirms the first stage for each state individually.

The second RD design focuses on the identity of representatives, and specifically on whether ward members belong to Scheduled Castes. Some ward member positions are reserved for SC candidates, meaning that only SCs may contest these seats. In seven states, the number of reserved positions is designed to be proportional to the SC share of the GP population based on the previous census. For a GP with n ward members, this generates discontinuities in the number of SC ward members at population shares of $(\frac{1}{2n}, \frac{3}{2n}, \ldots)$. For example, in a GP with 11 wards, the number of reserved SC seats increases from zero to one at an SC population share of 1/22, from one to two at 3/22, and so on. Restricting to the seven states that we can verify follow this rule, we estimate the same specification as in equation 1, redefining the running variable $p_{g,s}$ as the difference between the GP's SC population share and the nearest discontinuity.

Column (1) of Panel B of Table 1 and Panel A of Figure 2 validate the caste-based reservation design by estimating Equation 1 with actual number of SC representatives as the outcome and the caste reservation running variable. Crossing the reservation threshold increases the number of SC ward members by 0.41, corresponding to a 4.5 percentage point increase in the SC share of ward members (Column 2 of Panel B of Table 1).[5]

Two identification assumptions underpin our RD designs. First, the running variable must not be manipulable around the threshold. This is unlikely given the integrity of India's census process and the absence of prior evidence of manipulation (Asher and Novosad, 2020; Burlig and Preonas, 2021; Narasimhan and Weaver, 2024). Consistent with this, the test of Cattaneo et al. (2018) finds no evidence of bunching at the cutoff for either design (p-values of 0.99 and 0.59; Figure A1). Second, covariates should vary smoothly at the threshold. While this cannot be verified for all characteristics, the "Baseline covariates" columns of Table 1 show no significant discontinuities in village characteristics from the prior Census, supporting the validity of the design.[6]

new population census data since 2011. Our estimates thus reflect accumulated experience since the initial delimitation rather than only the present electoral cycle.

[5]Our main analysis focuses on reduced-form RD estimates rather than a fuzzy RD approach that instruments for the number or identity of ward members. Appendix B.2 shows that the results are unchanged using fuzzy RD.

[6]Another concern is that other program or funding eligibility rules may coincide with some of the thresholds we exploit. We searched for such cases and removed a case we identified (Uttar Pradesh, 1,000-person threshold). However, any such overlap would typically bias us toward detecting effects, which we do not

For brevity, we introduce the outcome datasets alongside the analysis in Section 4, with additional details in Appendix B.1. Most of the datasets used in the paper include unique identifiers from the Ministry of Panchayati Raj's Local Government Directory, enabling near-perfect matches. For data without standardized identifiers, we combine fuzzy name-matching algorithms with manual verification where automated matching fails, following the procedure described in Narasimhan and Weaver (2024). The match rates typically exceed 95%, and the likelihood of a successful match is unrelated to the discontinuities (Table A3; see Appendix B.1.9 for details), making bias from matching unlikely.

4 Results

4.1 Implementation of local government projects

Local governments in India manage a wide range of public projects. The National Rural Employment Guarantee Scheme is especially important, where GP leaders play a central role in proposing workfare projects, hiring workers, and overseeing implementation. In a typical GP, NREGS spending is comparable to the rest of the local government budget combined, making it a central policy domain and a useful lens for broader governance. Denser representation could improve access to workfare by creating more advocates for citizens or improving program efficiency, while greater representation of marginalized groups may shift who benefits.

We use annual, GP-level administrative data from the Ministry of Rural Development for 2016 to 2023 (Ministry of Rural Development, 2016-2020b) to study how hyperlocal representation affects NREGS implementation. This includes data on job cards issued, person-days of work, labor and material expenditures, and project completion. All outcomes are normalized by GP population (e.g., labor expenditure per capita). To address multiple inference concerns, we follow Kling et al. (2007) and construct a standardized index aggregating these outcomes, reporting effects on individual outcomes in the appendix.

Column (1) of Panel A of Table 2 and Panel (b) of Figure 1 estimate the first regression discontinuity specification (representative density), but find no effect on this index. This null estimate is precise, where the upper bound of the 95% confidence interval (0.017 SD) rules out even modest gains. Panel B of Table 2 and Panel (b) of Figure 2 estimate the representative identity RD specification and find similarly precise nulls. We also do not detect effects on any components of the index individually (Table A4).

Representative density or identity may still have distributional effects even if average

observe, and our results are not driven by any single threshold.

project outcomes are unchanged, such as if benefits shift toward more marginalized groups. We test this using two approaches. First, we use novel data from the Gram Manchitra initiative, which records the GPS location of 21 million NREGS projects completed between 2016 to 2023. We examine whether projects become more spatially dispersed within GPs, which would be consistent with reallocating benefits away from more privileged areas. We measure dispersion using the mean distance between projects within a GP (in kilometers), but Column (2) of Table 2 shows no effect of either treatment. Second, Columns (7) and (8) of Table A4 report caste-disaggregated effects on job cards and person-days of work. If either treatment led to targeted within-group benefits, we would expect relative gains for SC households, but we find no such effects under either design.

The implementation of NREGS is a domain in which ward members would be expected to play a role in project identification and oversight, and where political intermediation plausibly matters. The absence of effects here narrows the set of mechanisms through which expanded representation could operate, motivating our examination of intermediation and oversight in the next sections.

4.2 Intermediation in access to government benefits

A second role envisioned for hyperlocal representatives is helping constituents access public resources and welfare benefits, where they may provide information, assist in application processes, or advocate for citizen claims with bureaucrats or other politicians (Kruks-Wisner, 2018; Bussell, 2019). Such intermediation may be especially valuable for marginalized groups who lack access to political networks and may therefore benefit from representatives from their own identity group (Auerbach et al., 2023).

We measure intermediation with data from the Mission Antyodaya initiative, which reports village-level counts of beneficiaries of major government programs in 2019–2020 and 2022–2023 (Ministry of Rural Development, 2019). These programs span central and state government initiatives, including ration cards providing access to subsidized food, widow and old-age pensions, electricity and LPG connections, maternal cash transfers, housing assistance, piped water, and zero-balance bank accounts (see Appendix B.1.2 for details). This data was compiled by the central government based on departmental administrative records (e.g., Department of Food and Civil Supplies records of households with ration cards).

Following the approach used for NREGS, we construct a standardized index of welfare receipt outcomes (Kling et al., 2007), while reporting disaggregated results in supplementary tables (Table A5). Column (3) of Table 2 shows no effect of either increased representative density or greater SC representation on this index (Panel (d) of Figures 1 and 2). The esti-

mates are highly precise due to an effective sample size exceeding 75,000 observations. This contrasts with cross-sectional evidence from India linking denser representation to better service outcomes (Auerbach, 2019). Taken together with the NREGS findings, these results suggest that increasing hyperlocal representation—either in number or identity—does not translate into greater access to welfare or workfare benefits for citizens,[7] despite these being domains where political intermediation is thought to be central. However, we cannot distinguish whether hyperlocal representatives exert limited effort or lack the capacity to be effective intermediaries.

4.3 Accountability and monitoring

A final potential role for hyperlocal representatives is promoting accountability by monitoring more powerful political actors or bureaucrats. Their presence could deter corruption or mismanagement by increasing scrutiny, particularly when representatives come from groups that may otherwise lack access to power. At the same time, the effects are theoretically ambiguous: additional representatives may also expand rent-seeking.

To assess effects on accountability, we use two sources of audit data. First, we use novel data on GP-level financial audits conducted annually by the Ministry of Panchayati Raj in fiscal years 2020–2022. Audits are conducted annually by district-level audit teams, who review compliance with financial and procedural norms, classify irregularities into 19 standardized categories, and report violations to executive authorities. Second, we use data from NREGS social audits conducted between 2016 and 2024. These are conducted by trained laypersons from outside the village, who inspect recent works and interview residents to verify payments against official records, and Pande et al. (2025) shows they are highly effective in detecting corruption. The social audits are particularly well-suited to pick up cases where ward members may have an effect, such as reducing the cases of constituents facing non-payment for work. Appendix B.3 provides additional detail and shows that these two independent audit systems exhibit a strong positive relationship in detected violations.

Columns (4) and (5) of Table 2 (Panels (e) and (f) of Figures 1 and 2) report effects on the total violations detected in each audit, while Appendix Tables A6 and A7 disaggregate by violation type, focusing on the most common categories. While one estimate (citizen grievances) in Appendix Table A7 is marginally significant at the 10% level for additional SC representatives, this is consistent with chance given the number of statistical tests. Overall, the results suggest that hyperlocal representatives have limited effects on corruption and oversight.

[7] Jeong et al. (2023) find that election to local office increases NREGS self-dealing, suggesting reallocation by winner identity but no aggregate effects large enough to detect here.

4.4 Interpretation and Mechanisms

Our results indicate that additional hyperlocal representatives have little effect on core governance functions. One plausible interpretation is that these representatives lack the authority, information, or incentives needed to influence outcomes, but it could also be a function of our empirical approach. We conduct seven tests to evaluate these explanations.

First, representation may exhibit diminishing marginal returns, where additional representatives may matter most at low baseline levels; estimates like ours that combine many margins could miss those effects (Tests 1–2). Second, the changes in representation that we observe may be too small to detect effects (Test 3). Third, the marginal representative may be quite different from the average ward member, such that our estimates are uninformative about ward members generally (Test 4). Fourth, representatives may become more effective with experience, so pooling across their term could attenuate estimates (Test 5). Tests 6 and 7 provide positive evidence of ward members having limited influence over core governance outcomes.

Test 1: Diminishing Marginal Returns from Density Our main representation density RD specification in Equation 1 stacks multiple discontinuities, averaging across heterogeneous treatments (e.g., increases from 5 to 7 members or from 12 to 14 members). Our first test evaluates diminishing marginal returns by disaggregating these effects into more homogeneous treatments. Specifically, we group GPs based on the number of ward members to the left of their nearest population threshold and re-estimate Equation 1 separately within each group. For example, GPs with five or six members to the left correspond to discontinuities that increase representation from 5 to 7 or 6 to 9 members. If returns to representation diminish, marginal effects should be larger when baseline representation is low (e.g., 5 members) relative to higher (e.g., 15 members).

Panel (a) of Figure 3 plots the estimated coefficients by group for each of the five main outcomes from Table 2. Contrary to the diminishing-returns hypothesis, estimates are consistently near zero and statistically insignificant. Although we lack data for GPs with fewer than five ward members, the absence of detectable effects even at relatively low levels of representation suggests that additional ward members are largely ineffective.

Test 2: Diminishing Marginal Returns to Marginalized Representatives The second test applies the same logic to the second, caste-based representation design. As in Test 1, we bin the sample based on the change in SC representation induced by the nearest discontinuity and re-estimate Equation 1 within each bin for the identity RD. For example, the first bin corresponds to an increase in the number of SC-reserved seats from zero to one,

which we might expect to have the largest effect. However, Panel (b) of Figure 3 shows no evidence of impacts in any bin, providing further evidence against diminishing returns.

Test 3: Larger Shifts in Representation The third test examines whether our null estimates are due to the changes in representation being relatively small. We re-estimate the density RD restricting attention to discontinuities that induce larger proportional increases in density: the top 10%, 25%, and 50% of changes, corresponding to increases of at least 40%, 28.6%, and 18.1% in density, respectively. Panel (c) of Figure 3 again shows null results across all samples, indicating that even sizable increases in representation density do not affect outcomes.[8]

Test 4: Quality of marginal representatives The marginal representatives induced by our first research design may differ systematically from the average ward member (e.g., less educated), limiting the informativeness of our estimates to all ward members. We test this by examining whether average ward member characteristics change discontinuously at population thresholds under our first empirical strategy, reflecting systematic differences between the marginal and non-marginal representatives. For example, if marginal representatives are less educated than non-marginal ones, average education levels should decline to the right of the cutoff.

Panel A of Appendix Table A8 shows little evidence of such compositional changes, implying that marginal representatives do not differ significantly in education, age, or gender, with only a small increase in the likelihood of belonging to the OBC caste category. These results indicate that marginal representatives are broadly similar to incumbents along observable dimensions. This finding is also consistent with Test 1: if marginal representatives were systematically lower quality in outcome-relevant ways, treatment effects would vary with baseline representation, which we do not observe.

Test 5: Learning Ward members may become more effective with experience, such that pooling across their term masks stronger effects in later years when they have more experience. To test this hypothesis, we exploit cross-state variation in election timing and the long NREGS panel to estimate treatment effects on the NREGS index outcome in each year since the ward member was first elected. The estimates in Appendix Table A9 remain close to zero throughout representatives' terms, providing evidence against ward members either

[8]Appendix Figure A2 re-estimates each main specification by state. Of these estimates, 7 are statistically significant at the 5% level (five in the opposite direction of expectation), consistent with chance given the number of tests in this paper (195 tests involving governance outcomes), and with no systematic state-level patterns.

learning over time or being responsive to upcoming elections as they draw closer (consistent with a limited role of electoral discipline).

Test 6: Deliberative processes Our sixth test delves into the black box of local government decision-making by examining policy deliberations. We use administrative data on over 1.2 million Gram Panchayat Development Plan (GPDP) meetings held between 2019 and 2023. These are statutorily mandated forums in which citizens and elected representatives determine local development priorities for the coming year (e.g., roads, sanitation; see Appendix B.1.8 for details). If hyperlocal representatives influence governance outcomes, their effects should be most apparent at this agenda-setting stage.

Our data contain the list of development priorities that each meeting decided should be the focus of the GP in the upcoming year. A larger number of representatives should generate greater heterogeneity in preferences over these priorities. If members influence deliberations, this heterogeneity should increase the total number of priority areas. Yet applying our main specification for representative density, we find no effect (column (1) of Appendix Table A10). GPDP meetings are also intended to cover seven core topics, such as reviewing GP finances. Applying the same specification, expanded representation does not affect the number of core topics discussed (Column 2 of Appendix Table A10) or discussion of any individual topic (Appendix Table A11). However, we do observe that increased representative density significantly increases citizen attendance at GPDP meetings (columns 3 to 6). Taken together, these findings suggest that hyperlocal representatives influence participation in deliberative forums, but not the policy priorities that emerge from them, consistent with a limited role in governance.

Test 7: Voter turnout as revealed preference Our final test uses voter turnout as a revealed-preference measure of whether citizens value their hyperlocal representatives. In standard models of voter turnout (Downs, 1957; Riker and Ordeshook, 1968), an individual votes if the cost of voting C is outweighed by expressive benefits D and the expected instrumental benefit pb, where p is the probability of being pivotal and b is the benefit from the preferred candidate winning ($C < D + pb$). In our setting, an increase in the number of ward members reduces ward size while holding population fixed, and thus raises p for all voters in the GP. If voters value these positions ($b > 0$), turnout should increase.

Ward member elections are a setting in which pivotality is highly salient: 27% of contested elections in Uttar Pradesh are decided by 10 or fewer votes. Using data from the 2021 ward member elections in Uttar Pradesh, Columns (1) and (2) of Table A12 show that both the number of eligible voters per ward and margins of victory fall at the discontinuity. However,

Column (3) shows no change in turnout. Within the framework above, this absence of a turnout response despite higher pivotality implies that b is close to zero, consistent with a low perceived value of these positions.

These tests suggest that the limited effects of hyperlocal representatives reflect constraints inherent to the roles themselves rather than features of the empirical design. While ward members may play other roles we do not observe, such as mediating community conflicts, they do not appear to fulfill core governance functions envisioned in official training materials (Ministry of Rural Development, 2020a). Although these positions increase proximity between citizens and the state, it appears that political inclusion alone need not translate into improved governance.

5 Conclusion

Hyperlocal representatives constitute the largest class of elected officials globally, yet credible causal evidence on their effectiveness remains scarce. Studying village councils in rural India, we find little evidence that changing the density or identity of hyperlocal representatives affects public goods provision, welfare access, or oversight. The pattern of results suggest that, while increasing representation is normatively appealing, hyperlocal representatives may fail to exercise influence over substantive outcomes, functioning more as symbolic than as decision-making actors.

More broadly, our findings speak to a central question in political economy: when does political representation translate into effective power? Our results suggest that expanding representation without corresponding investments in authority, training, or incentives may yield limited returns, even when representatives are closely embedded in local communities. This is not obvious a priori, as even relatively disempowered representatives could still matter by conveying local information to higher-level officials, lending institutional legitimacy to citizen claims in interactions with bureaucrats, or serving as focal points for coordinating collective political action. Future research should further investigate how institutional design shapes the relationship between representation and governance, and identify the conditions under which political inclusion leads to durable improvements in accountability and development.

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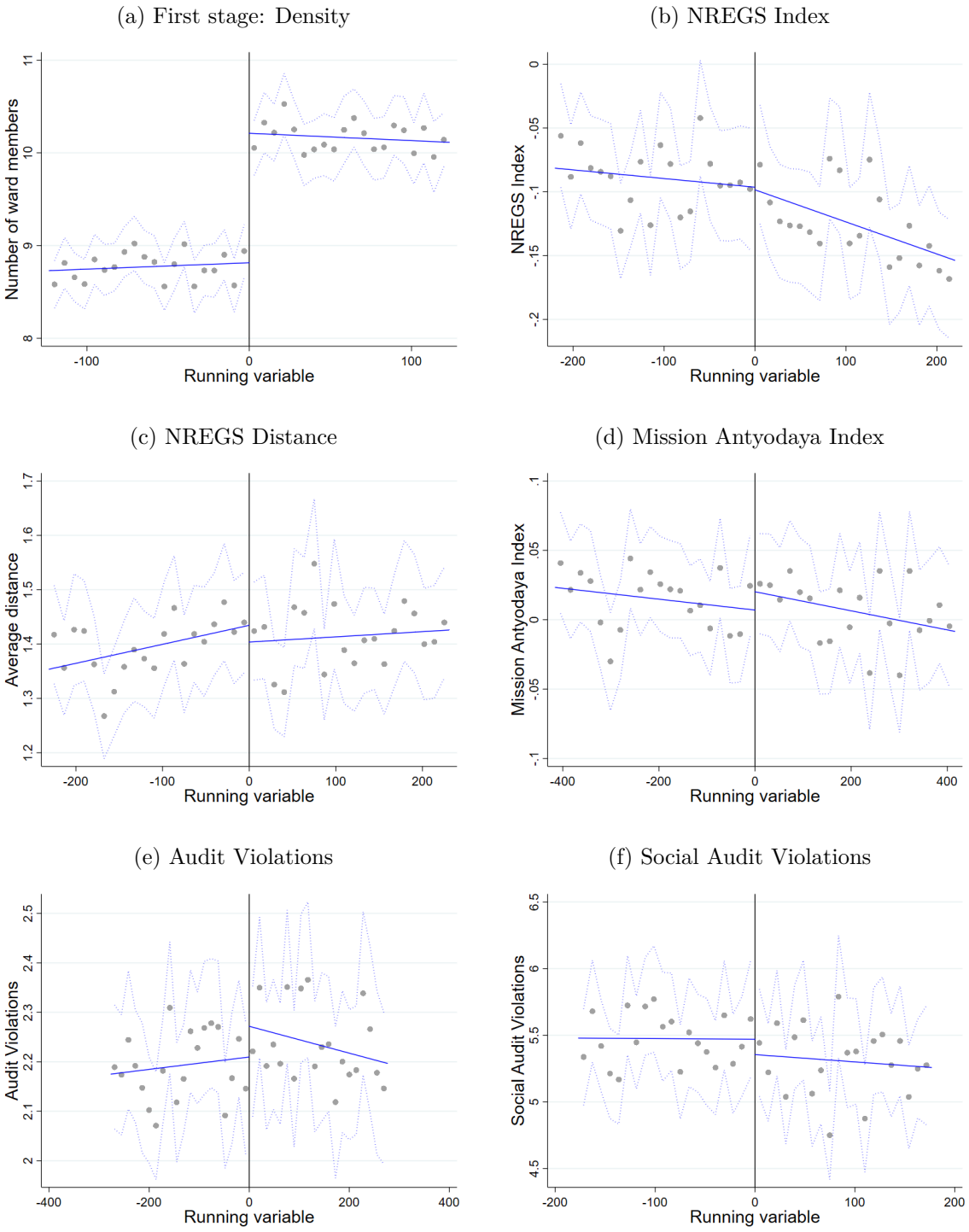
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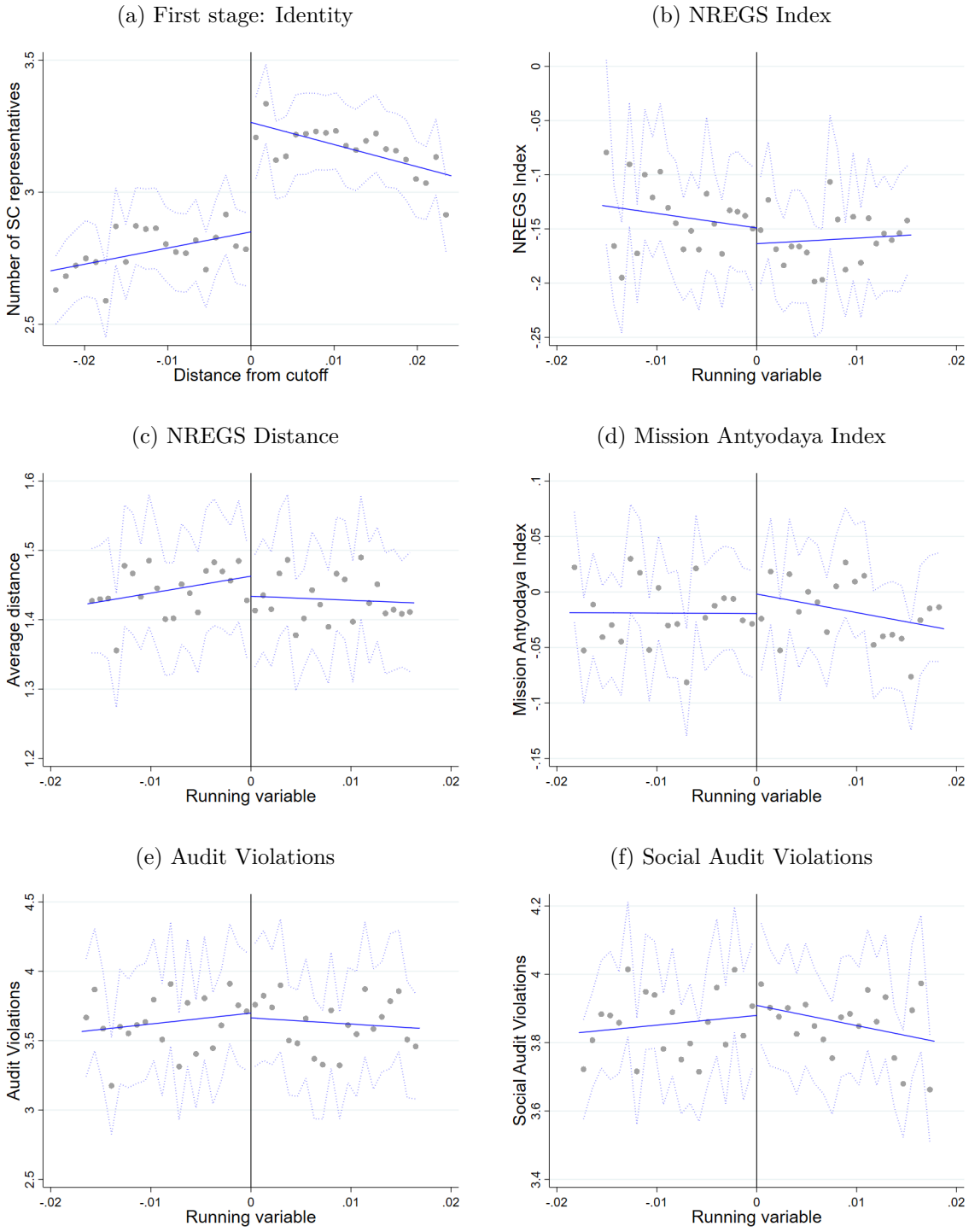
6 Figures and Tables

Figure 1: Density of political representation



Notes: These figures plot reduced-form regression discontinuity relationships for the density of political representation design. Panel (a) shows the first-stage relationship between the number of ward members and the running variable. Panels (b)-(f) show reduced-form effects on a standardized NREGS workfare index, mean distance between NREGS projects (in km), a standardized Mission Antyodaya welfare access index, total financial audit violations, and total social audit violations, respectively. Each panel plots binned means and local linear fits estimated separately on either side of the cutoff using triangular kernels and MSE-optimal bandwidths.

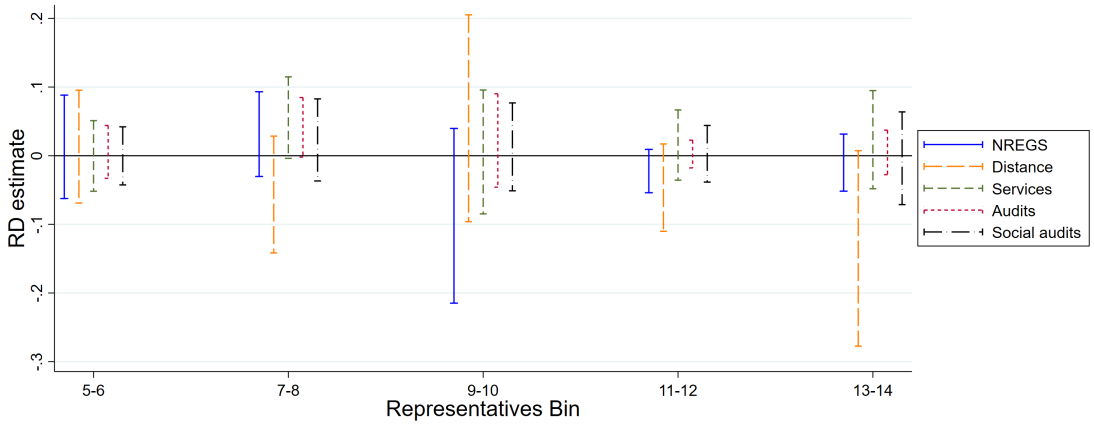
Figure 2: Representation of marginalized groups



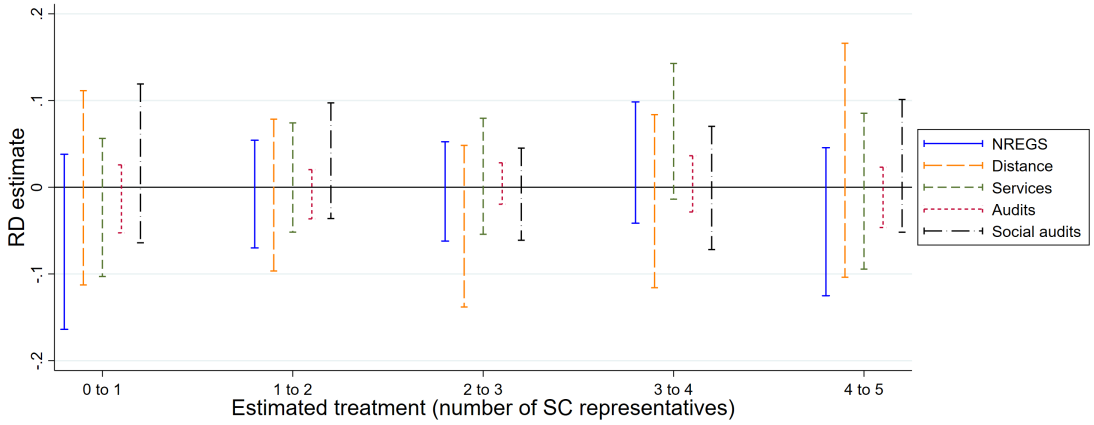
Notes: These figures plot reduced-form regression discontinuity relationships for the caste-based reservation design. Panel (a) shows the first-stage relationship between Scheduled Caste (SC) representation and the running variable. Panels (b)-(f) show reduced-form effects on a standardized NREGS workfare index, mean distance between NREGS projects (in km), a standardized Mission Antyodaya welfare access index, total financial audit violations, and total social audit violations, respectively. Each panel plots binned means and local linear fits estimated separately on either side of the cutoff using triangular kernels and MSE-optimal bandwidths.

Figure 3: Additional tests of mechanisms

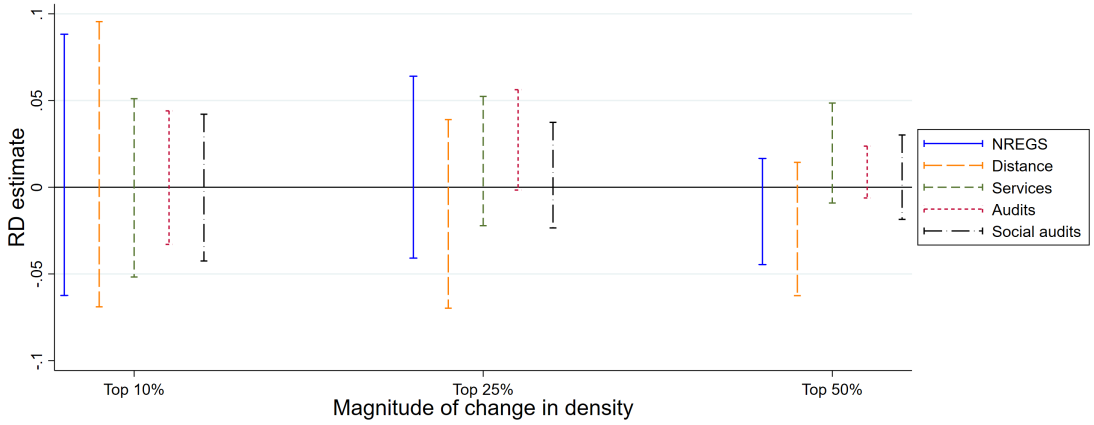
(a) Test 1: diminishing returns to density



(b) Test 2: diminishing returns to identity



(c) Test 3: Focus on larger proportional changes



Notes: These figures plot regression discontinuity estimates and corresponding confidence intervals for mechanism and heterogeneity analyses. Outcomes are standardized indices of NREGS workfare, mean distance between NREGS projects (in km), Mission Antyodaya welfare access, financial audit violations, and social audit violations; for distance and audit outcomes, indices are constructed by normalizing relative to the state-level mean and standard deviation. Panel (a) estimates effects separately by the number of ward members to the left of the nearest population cutoff (5-6, 7-8, 9-10, 11-12, and 13-14). For example, the first category (GPs with five or six members to the left) corresponds to discontinuities that increase representation from 5 to 7 or 6 to 9 members. Panel (b) applies the same approach to caste-based representation, grouping discontinuities by the change in the number of Scheduled Caste (SC) representatives. Panel (c) restricts the sample to discontinuities in the top 10, 25, and 50 percent of changes in the representative-to-population ratio. All estimates use local linear RD specifications with triangular kernels and MSE-optimal bandwidths.

Table 1: First stage and balance of baseline characteristics

Panel A: Additional political representatives							
	First stage	Baseline covariates (2011)					
	Total reps	Primary school	Middle school	Paved road	Electrified	SC pop.	Literate pop.
RD_Estimate	1.3875***	0.0084	-0.0012	0.0098	-0.0080	0.0000	-0.0011
	(0.0873)	(0.0059)	(0.0105)	(0.0102)	(0.0110)	(0.0034)	(0.0023)
	[0.000]	[0.153]	[0.912]	[0.337]	[0.467]	[0.997]	[0.634]
Dep var mean	10.200	0.888	0.574	0.744	0.713	0.228	0.600
Bandwidth	178.726	198.133	186.649	172.549	168.959	248.811	245.730
Effective Obs	25060	35534	33443	31021	30288	44139	43633
Panel B: Additional representation of marginalized groups							
	First stage		Baseline covariates (2011)					
	SC reps	SC frac	Primary school	Middle school	Paved road	Electrified	SC pop.	Literate pop.
RD_Estimate	0.4130***	0.0450***	-0.0109	-0.0027	-0.0033	0.0071	0.0061	-0.0004
	(0.0519)	(0.0047)	(0.0076)	(0.0094)	(0.0104)	(0.0116)	(0.0038)	(0.0027)
	[0.000]	[0.000]	[0.151]	[0.770]	[0.751]	[0.541]	[0.105]	[0.869]
Dep var mean	3.164	0.294	0.858	0.545	0.723	0.644	0.243	0.571
Bandwidth	0.024	0.022	0.012	0.018	0.013	0.014	0.015	0.013
Effective Obs	49668	42510	25597	39305	27909	29325	32226	28871

Note: This table reports regression discontinuity estimates validating the two empirical designs and testing balance in pre-determined characteristics. Panel A examines population-based thresholds in state Panchayati Raj Acts: the first column reports the first-stage effect on the total number of ward members, and remaining columns test balance in baseline GP characteristics from the 2011 Census. Panel B examines caste-based reservation thresholds: the first two columns report effects on the number and share of SC ward members, followed by balance tests for the same covariates. Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Main outcomes

Panel A: Effect of additional political representatives					
	Workfare index	Workfare project dispersion	Benefit programs index	Audit violations	Social audit violations
RD_Estimate	-0.0123	-0.0497	0.0201	0.0358	-0.0539
	(0.0144)	(0.0311)	(0.0136)	(0.0385)	(0.0978)
	[0.393]	[0.110]	[0.139]	[0.353]	[0.582]
Dep var mean	-0.149	1.421	0.007	1.952	4.876
Bandwidth	226.753	262.824	364.781	257.071	234.470
Effective Obs	268125	292777	116978	542027	156257
Panel B: Effect of additional representation of marginalized groups					
	Workfare index	Workfare project dispersion	Benefit programs index	Audit violations	Social audit violations
RD_Estimate	-0.0136	-0.0317	0.0079	-0.0883	0.0357
	(0.0172)	(0.0298)	(0.0166)	(0.0683)	(0.0701)
	[0.427]	[0.287]	[0.636]	[0.196]	[0.611]
Dep var mean	-0.157	1.430	-0.017	2.193	3.872
Bandwidth	0.018	0.016	0.019	0.014	0.013
Effective Obs	291012	245623	77239	471845	121463

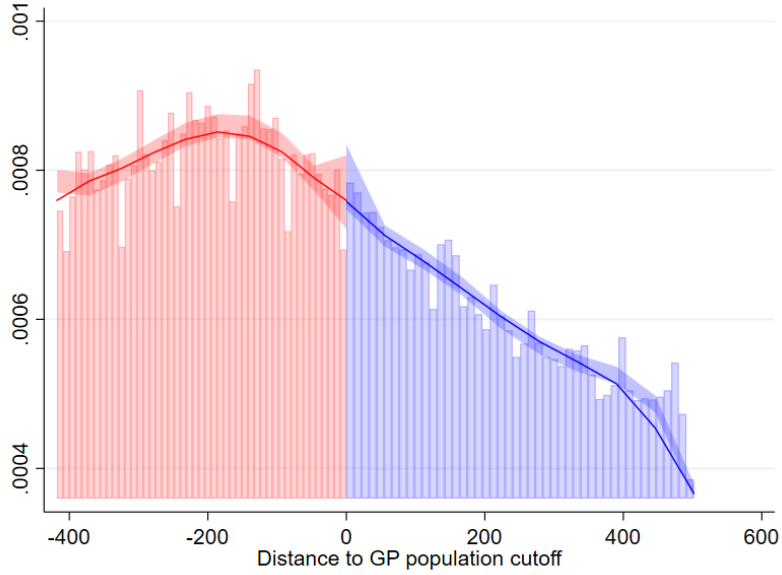
Note: This table reports regression discontinuity estimates of the effects of hyperlocal representation on main governance outcomes. Panel A reports effects of increases in the number of ward members, while Panel B reports effects of increases in representation from Scheduled Castes (SC). Outcomes include a standardized index of NREGS workfare implementation, spatial dispersion of NREGS projects (in km), a standardized index of access to eight welfare programs from Mission Antyodaya, and total audit violations from financial audits. All outcomes are measured at the gram panchayat level and standardized where indicated. Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

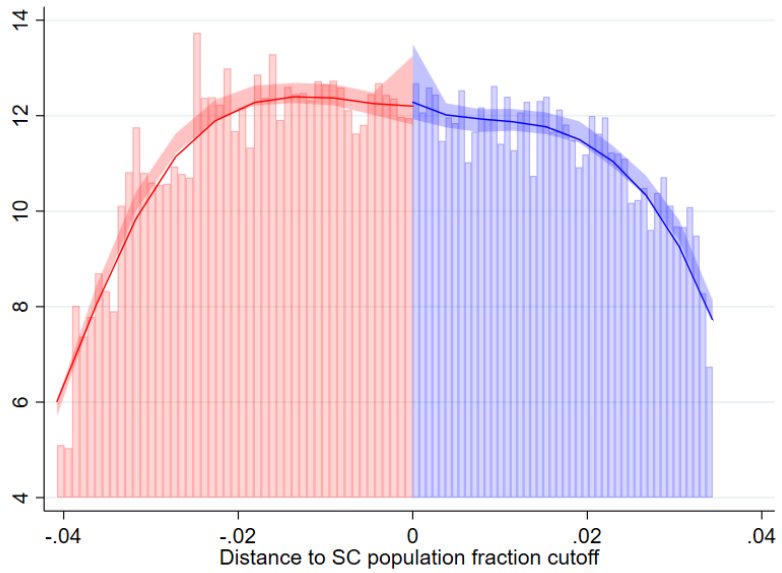
Appendix: For Online Publication

A Appendix Figures and Tables

Figure A1: Distribution of the running variable

(a) Manipulation test (Density)



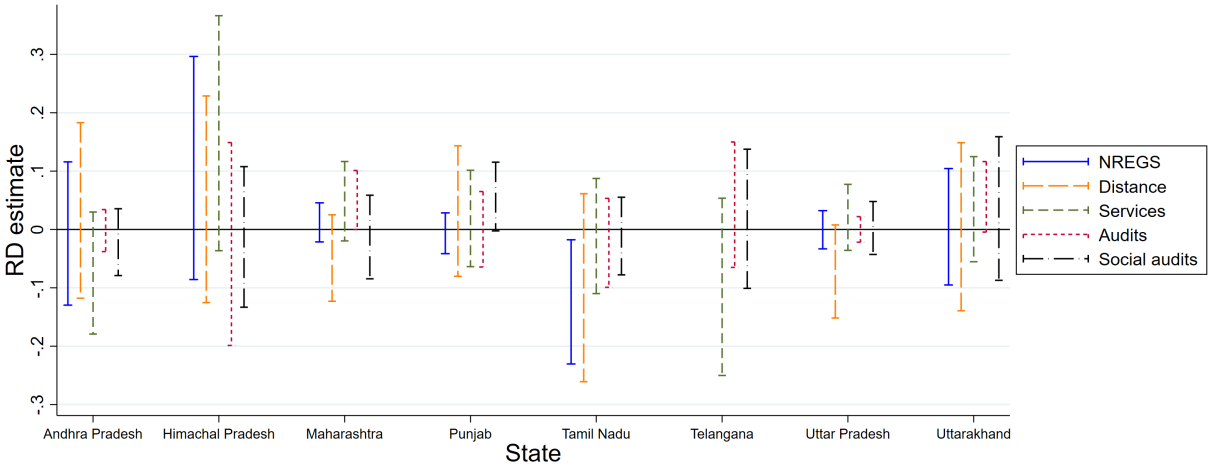


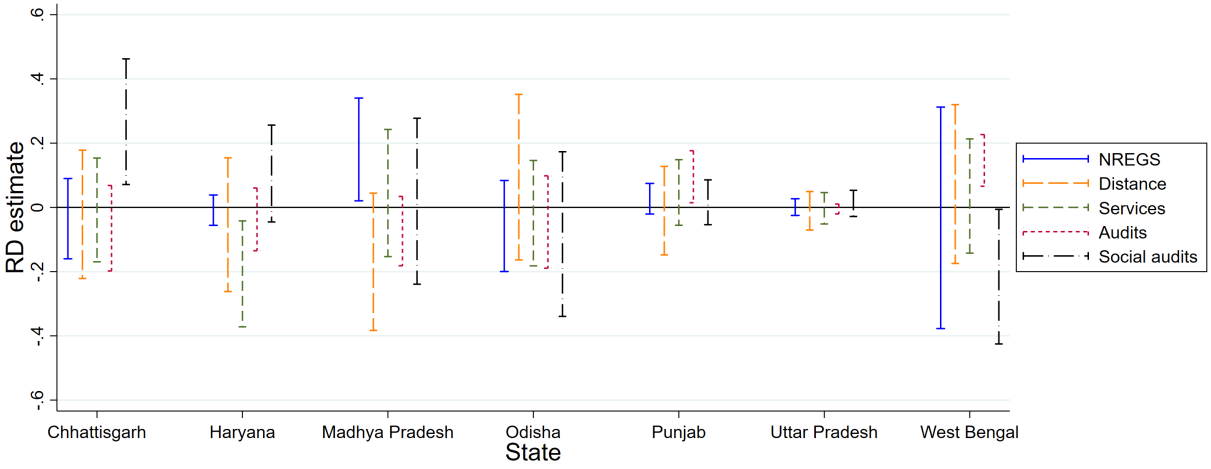
(b) Manipulation test (Representative identity)

Notes: These figures plot the distribution of the running variables around their respective cutoffs and a non-parametric regression for each half of the distribution in order to test for a discontinuity in the running variables around the threshold (Cattaneo et al., 2020).

Figure A2: Estimated effects by states

(a) Representative Density





(b) Representative identity

Notes: These figures plot state-specific regression discontinuity estimates and corresponding confidence intervals, providing state-level analogues to the pooled estimates in Table 2. Outcomes are standardized indices of NREGS workfare, mean distance between NREGS projects, Mission Antyodaya welfare access, financial audit violations, and social audit violations; distance and audit outcomes are normalized using state-level means and standard deviations. Panel (a) reports effects of increases in representative density, and Panel (b) reports effects of increases in representation from marginalized groups. NREGS data are unavailable for Telangana, so NREGS and distance outcomes are not shown for that state. All estimates use local linear RD specifications with triangular kernels and MSE-optimal bandwidths.

State	Population (2025 est.)	Rules relating number of ward members to GP population	SC member rule
Andhra Pradesh	54.0 million [3.75%]	Population below 1500: 9 members Above 1500: Increase by 2 members per 1500 people	No
Chhattisgarh	25.5 million [2.11%]		Yes
Haryana	25.4 million [2.09%]		Yes
Himachal Pradesh	7.9 million [0.55%]	Less than 1750: 5 1750-2749: 7 2750-3749: 9 3750-4749: 11 4750+: 13	No
Madhya Pradesh	72.6 million [6.00%]		Yes
Maharashtra	126.6 million [8.79%]	Less than 1500: 7 Above 1500: Increase by 2 per 1500	No
Odisha	41.9 million [3.47%]		Yes
Punjab	30.8 million [2.14%]	Less than 1000: 5 1000-1999: 7 2000-4999: 9 5000-9999: 11 10000+: 13	Yes
Tamil Nadu	78.1 million [5.42%]	Less than 2000: 6 2000-5999: 9 6000-9999: 12	No
Telangana	40.6 million [2.82%]	Less than 1500: 7 1500-2999: 8 3000-4500: 9	No
Uttar Pradesh	248.4 million [17.25%]	Less than 1000: 9 1000-1999: 11 2000-2999: 13 3000+: 15	Yes
Uttarakhand	12.1 million [0.84%]	Less than 500: 5 500-999: 7 Above 1000: Increase by 2 per 1000	No
West Bengal	91.3 million [7.55%]		Yes

Table A1: Ward Member Rules and Population of Sample States (2025)

Note: This table summarizes state-specific rules governing the number of ward members and caste-based reservation policies across the states in the sample, along with state population sizes. Population figures are 2025 estimates, with each state's share of India's population reported in brackets. Ward member rules describe population thresholds and corresponding changes in the number of ward members at the gram panchayat level. The final column indicates whether Scheduled Caste (SC) reservation rules for ward members apply in the state.

Table A2: First stage by state

Panel A: Additional political representatives								
	Andhra Pradesh	Himachal Pradesh	Maharashtra	Punjab	Tamil Nadu	Telangana	Uttar Pradesh	Uttarakhand
RD_Estimate	0.8715***	1.2587***	1.1969***	1.1847***	2.6522***	1.0257***	1.5446***	0.3719***
	(0.1373)	(0.3289)	(0.1605)	(0.0914)	(0.1091)	(0.1696)	(0.1099)	(0.1247)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]
Dep var mean	9.510	7.400	8.409	6.948	8.997	9.430	12.185	7.249
Bandwidth	412.241	196.738	280.873	226.449	429.034	248.922	188.643	118.286
Effective Obs	3999	554	3224	3331	2771	1554	13407	2097
Panel B: Additional representation of marginalized groups								
	Chhattisgarh	Haryana	Madhya Pradesh	Odisha	Punjab	Uttar Pradesh	West Bengal	
RD_Estimate	0.0452**	0.0360**	0.0393**	0.0363**	0.0917***	0.0438***	0.0781*	
	(0.0201)	(0.0183)	(0.0159)	(0.0185)	(0.0177)	(0.0081)	(0.0415)	
	[0.025]	[0.049]	[0.014]	[0.049]	[0.000]	[0.000]	[0.060]	
Dep var mean	0.195	0.287	0.187	0.246	0.423	0.315	0.327	
Bandwidth	0.020	0.020	0.007	0.013	0.037	0.012	0.011	
Effective Obs	1736	1865	1317	1356	3110	15446	565	

Note: This table reports regression discontinuity estimates for the first-stage for the two empirical designs. Panel A examines the relationship between the first running variable (based on GP population) and the number of ward members. Panel B examines the relationship between the second running variable (based on SC population share) and the number of SC ward members. Ward member rosters are only observed for a subset of GPs based on data availability. All estimates use local linear RD specifications with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014). Standard errors are clustered at the GP level and reported in parentheses.

Table A3: Match rates

	Match rate		Match probability		
	Full sample	In sample	RD estimate	SE	p-value
Panel A: Additional political representation analysis					
Census	99.90%	100%			
Elections	95.97%	96.61%	.00279	(.00654)	.67
Financial Audits	99.32%	99.54%	-.00036	(.00113)	.749
GPDP Meetings	99.98%	99.98%	-.00009	(.00024)	.707
Mission Antyodaya	94.58%	95.82%	-.00189	(.00272)	.487
NREGS	90.34%	88.64%	-.00048	(.00639)	.941
NREGS (location)	90.32%	88.62%	-.00053	(.00636)	.934
Social audits (NREGS)	87.23%	86.32%	.00766	(.00714)	.284
Ward member roster	93.72%	92.39%	-.00885	(.00607)	.145
Panel B: Additional representation of marginalized groups analysis					
Census	99.88%	99.84%			
Elections	95.97%	96.39%	-.00508	(.00542)	.348
Financial Audits	98.95%	98.93%	-.00256	(.00217)	.239
GPDP Meetings	99.89%	99.91%	.00051	(.00071)	.467
Mission Antyodaya	97.94%	98.36%	.00304	(.00208)	.144
NREGS	93.98%	93.40%	.01053	(.0057)	.065
NREGS (location)	93.94%	93.35%	.00987	(.00576)	.086
Social audits (NREGS)	72.44%	81.18%	.01157	(.00949)	.223
Ward member roster	93.91%	97.55%	-.0039	(.00347)	.261

Panel A examines match rates for the analysis of additional political representation, while Panel B examines match rates for the analysis of additional representation from marginalized groups. Column (1) reports the match rate between the local government directory data and the listed data set for all gram panchayats in the sample for each panel (8 states in Panel A and 7 in Panel B). Column (2) reports the match rate for gram panchayats within the typical RD bandwidth for each panel. Columns (3) through (5) test for differential matching around the discontinuity. Column (3) reports regression discontinuity estimates for an indicator equal to one if the gram panchayat is successfully matched to the listed data set, with standard errors in column (4). Column (5) reports p-values for the corresponding RD estimates.

Table A4: Effects on NREGS

	Overall						Marginalized	
Panel A: Effect of additional political representatives								
	Workfare index	Job cards	Person days	Labor expenditure	Material expenditure	Total assets	Jobcards (SC)	Person days (SC)
RD_Estimate	-0.0123	-0.0026	-0.0625	-13.1579	-2.6270	0.0501	-0.0010	-0.2303
	(0.0144)	(0.0018)	(0.0972)	(17.0209)	(8.2351)	(0.2894)	(0.0059)	(0.1522)
	[0.393]	[0.142]	[0.520]	[0.439]	[0.750]	[0.863]	[0.858]	[0.130]
Dep var mean	-0.149	0.164	3.329	576.220	234.842	15.386	0.212	4.202
Bandwidth	226.753	288.674	229.679	189.745	194.651	323.827	317.640	259.281
Effective Obs	268125	243150	195122	153497	157386	375295	259104	214156
Panel B: Effect of additional representation of marginalized groups								
	Overall						Marginalized	
	Workfare index	Job cards	Person days	Labor expenditure	Material expenditure	Total assets	Jobcards (SC)	Person days (SC)
RD_Estimate	-0.0136	0.0003	-0.0408	-10.8306	0.5251	-0.5150	0.0021	-0.0002
	(0.0172)	(0.0018)	(0.0549)	(13.5314)	(6.5563)	(1.6303)	(0.0055)	(0.1273)
	[0.427]	[0.870]	[0.458]	[0.423]	[0.936]	[0.752]	[0.698]	[0.999]
Dep var mean	-0.157	0.138	2.737	557.293	226.881	29.520	0.190	3.629
Bandwidth	0.018	0.015	0.024	0.016	0.017	0.015	0.015	0.016
Effective Obs	291012	184517	278586	183108	199466	244239	181549	185226

Note: This table reports regression discontinuity estimates of the effects of hyperlocal representation on NREGS workfare outcomes. Panel A reports effects of increases in the number of ward members, and Panel B reports effects of increases in Scheduled Caste (SC) representation. Columns (1) examines effects on a standardized index of the other variables. The outcome in column (2) is the per capita number of job cards, while column (3) is per capita days of NREGS work provided in the GP. Columns (4) and (5) measure total expenditure on labor and materials, while column (6) measures the total assets created by the NREGS program. Columns (7) and (8) look at the per capita job card and days worked outcomes only among SC households. Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Effects on program access

	Programs index	Jan Dhan	Ration card	LPG	Pension	Saubhagya (elec.)	PMMVY	Housing benefits	Piped water
Panel A: Effect of additional political representatives									
RD_Estimate	0.0201	0.0003	0.0057	0.0038	0.0032	0.0041	0.0002	0.0032	0.0098
	(0.0136)	(0.0035)	(0.0057)	(0.0035)	(0.0040)	(0.0036)	(0.0002)	(0.0051)	(0.0076)
	[0.139]	[0.932]	[0.314]	[0.269]	[0.416]	[0.248]	[0.318]	[0.531]	[0.198]
Dep var mean	0.007	0.351	0.500	0.243	0.262	0.152	0.015	0.222	0.293
Bandwidth	364.781	388.755	243.368	340.465	224.583	255.367	406.185	253.235	175.701
Effective Obs	116978	123853	80777	110039	74778	84622	129056	84042	58879
Panel B: Effect of additional representation of marginalized groups									
	Programs index	Jan Dhan	Ration card	LPG	Pension	Saubhagya (elec.)	PMMVY	Housing benefits	Piped water
RD_Estimate	0.0079	0.0014	-0.0029	0.0026	-0.0089*	0.0064	-0.0005	0.0014	-0.0056
	(0.0166)	(0.0051)	(0.0074)	(0.0052)	(0.0048)	(0.0044)	(0.0004)	(0.0060)	(0.0070)
	[0.636]	[0.776]	[0.697]	[0.616]	[0.063]	[0.143]	[0.224]	[0.813]	[0.427]
Dep var mean	-0.017	0.364	0.528	0.296	0.254	0.191	0.016	0.239	0.166
Bandwidth	0.019	0.016	0.012	0.012	0.010	0.014	0.015	0.016	0.010
Effective Obs	77239	64188	48918	48372	40921	58588	60440	63805	42302

Note: This table reports regression discontinuity estimates of the effects of hyperlocal representation on access to public programs. Panel A reports effects of increases in the number of ward members, and Panel B reports effects of increases in Scheduled Caste (SC) representation. Columns (1) examines effects on a standardized index of the other variables. The outcome in column (2) is the number of zero-balance bank accounts under the Jan Dhan initiative, while column (3) is Below Poverty Line (BPL) ration cards providing access to subsidized food grains. Columns (4) and (5) measure liquefied petroleum gas (LPG) connections (Pradhan Mantri Ujjwala scheme) and pensions for the elderly, widows, and the disabled (National Social Assistance Programme), while column (6) measures household electricity connections under the Saubhagya scheme (Pradhan Mantri Sahaj Bijli Har Ghar Yojana). Columns (7) and (8) look at a Rs. 5000 cash transfer for pregnant women and mothers (Pradhan Mantri Matru Vandana Yojana) and housing subsidies or waitlist status under Pradhan Mantri Awaas Yojana or state schemes. Column (9) examines publicly provided piped water connections (Jal Jeevan Mission). Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Effects on audit violations

Panel A: Effect of additional political representatives					
	Tot viol.	No viol.	Rule viol.	Non-prod of records	Irregularities
RD_Estimate	0.0358	0.0060	0.0104	0.0034	-0.0021
	(0.0385)	(0.0061)	(0.0065)	(0.0054)	(0.0059)
	[0.353]	[0.319]	[0.107]	[0.526]	[0.719]
Dep var mean	1.952	0.568	0.278	0.270	0.096
Bandwidth	257.071	142.066	264.773	378.746	155.127
Effective Obs	542027	304913	556206	783940	333317
Panel B: Effect of additional representation of marginalized groups					
	Tot viol.	No viol.	Rule viol.	Non-prod of records	Irregularities
RD_Estimate	-0.0883	0.0004	-0.0003	0.0008	-0.0002
	(0.0683)	(0.0049)	(0.0060)	(0.0083)	(0.0023)
	[0.196]	[0.928]	[0.960]	[0.925]	[0.919]
Dep var mean	2.193	0.660	0.241	0.274	0.025
Bandwidth	0.014	0.011	0.017	0.012	0.011
Effective Obs	471845	369995	561367	384859	345770

Note: This table reports regression discontinuity estimates of the effects of hyperlocal representation on financial misconduct, as measured by audits of the gram panchayat. Panel A reports effects of increases in the number of ward members, and Panel B reports effects of increases in Scheduled Caste (SC) representation. Columns (1) examines effects on the total number of detected violations, while column 2 looks at whether any violations were detected. Columns (3) to (5) measure the total number of the three most common violation types: procedural rule violations, refusals to provide records (a potential indicator of an attempt to avoid revealing corruption), and financial irregularities. Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Effects on NREGS social audits violations

Panel A: Effect of additional political representatives					
	Total issues	Financial misapprop.	Financial deviation	Process violation	Citizen grievances
RD_Estimate	-0.0539	-0.0250	-0.0191	-0.0772	0.0007
	(0.0978)	(0.0335)	(0.0255)	(0.0506)	(0.0145)
	[0.582]	[0.456]	[0.455]	[0.127]	[0.962]
Dep var mean	4.876	0.630	0.828	2.627	0.657
Bandwidth	234.470	218.432	239.059	368.949	336.319
Effective Obs	156257	145904	159422	242194	221956
Panel B: Effect of additional representation of marginalized groups					
	Total issues	Financial misapprop.	Financial deviation	Process violation	Citizen grievances
RD_Estimate	0.0357	-0.0017	-0.0178	0.0437	0.0239
	(0.0701)	(0.0072)	(0.0148)	(0.0521)	(0.0208)
	[0.611]	[0.819]	[0.230]	[0.402]	[0.250]
Dep var mean	3.872	0.105	0.445	2.540	0.737
Bandwidth	0.013	0.013	0.011	0.012	0.014
Effective Obs	121463	120337	96170	111605	128269

Note: This table reports regression discontinuity estimates of the effects of hyperlocal representation on financial misconduct, as measured by audits of the gram panchayat. Panel A reports effects of increases in the number of ward members, and Panel B reports effects of increases in Scheduled Caste (SC) representation. Columns (1) examines effects on the total number of detected violations. Columns (2) to (5) measure the total number of the violation types most tightly linked to corruption: financial misappropriation, deviations in financial records, process violations, and citizen grievances (often about theft of wage payments). Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Characteristics of elected members

Panel A: Effect of additional political representatives

				Caste		
	Education	Age	Female	SC	OBC	General
RD_Estimate	-0.0071	-0.2631	-0.0039	-0.0069	0.0175*	-0.0129
	(0.0231)	(0.2202)	(0.0064)	(0.0066)	(0.0090)	(0.0098)
	[0.758]	[0.232]	[0.545]	[0.295]	[0.053]	[0.189]
Dep var mean	1.499	41.074	0.457	0.269	0.367	0.323
Bandwidth	326.941	203.496	222.682	237.028	210.199	211.676
Effective Obs	31240	13072	22631	24035	21430	21523

Panel B: Effect of additional representation of marginalized groups

				Caste		
	Education	Age	Female	SC	OBC	General
RD_Estimate	-0.0052	-0.1225	-0.0048	0.0450***	-0.0150**	-0.0209***
	(0.0254)	(0.1901)	(0.0048)	(0.0048)	(0.0076)	(0.0070)
	[0.838]	[0.519]	[0.318]	[0.000]	[0.048]	[0.003]
Dep var mean	1.436	41.060	0.436	0.294	0.405	0.229
Bandwidth	0.013	0.013	0.014	0.021	0.013	0.014
Effective Obs	23415	17225	26181	40849	24982	26239

Note: This table reports estimates of how the changes in representation induced by the regression discontinuity designs we study affect the average characteristics of elected ward members. Panel A reports effects of increases in the number of ward members, while Panel B reports effects of increases in representation from Scheduled Castes (SC). Column 1 reports effects on the average education levels of elected members. The education variable ranges from 0 (illiterate) to 7 (PhD), using data from the Uttar Pradesh 2021 elections and rosters of ward members from Gram Manchitra. Column 2 reports effects on the average age of ward members, while column 3 repots the fraction who are female. Columns 4 to 6 examine the fraction of ward members who are from different caste groups (Scheduled Caste, Other Backwards Classes, General Caste). All outcomes are measured at the gram panchayat level. Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Effects on NREGS by year since election

Panel A: Effect of additional political representatives					
	0 Years	1 Years	2 Years	3 Years	4 Years
RD_Estimate	-0.0009	-0.0183	0.0001	-0.0053	0.0053
	(0.0142)	(0.0114)	(0.0101)	(0.0120)	(0.0184)
	[0.952]	[0.110]	[0.992]	[0.657]	[0.774]
Dep var mean	-0.138	-0.130	-0.150	-0.193	0.012
Bandwidth	282.356	272.821	304.917	341.151	236.933
Effective Obs	37651	50981	62722	46208	36713
Panel B: Effect of additional representation of marginalized groups					
	0 Years	1 Years	2 Years	3 Years	4 Years
RD_Estimate	0.0130	0.0049	0.0080	-0.0021	-0.0060
	(0.0138)	(0.0103)	(0.0101)	(0.0133)	(0.0136)
	[0.344]	[0.635]	[0.429]	[0.873]	[0.659]
Dep var mean	-0.392	-0.291	-0.351	-0.395	-0.397
Bandwidth	0.016	0.016	0.014	0.017	0.016
Effective Obs	27651	47440	42614	27868	26999

Note: This table reports regression discontinuity estimates of the effects of hyperlocal representation on NREGS outcomes by time since the most recent gram panchayat election. Columns report effects estimated separately by year since election. Panel A reports effects of increases in the number of ward members, and Panel B reports effects of increases in Scheduled Caste (SC) representation. The outcome is the standardized NREGS workfare index. All estimates use local linear RD specifications with triangular kernels and MSE-optimal bandwidths. Standard errors are clustered at the gram panchayat level and reported in parentheses; p-values are reported in brackets. Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Gram Panchayat Development Plan Meetings

Panel A: Effect of additional political representatives						
	Outcomes		Attendance			
	Total focus areas	Topics covered	Total	Women	SC	ST
RD_Estimate	0.0295	-0.0004	8.0379**	1.8842*	0.3472	1.1773**
	(0.0525)	(0.0123)	(3.2005)	(1.0769)	(0.9222)	(0.5571)
	[0.575]	[0.975]	[0.012]	[0.080]	[0.707]	[0.035]
Dep var mean	2.679	5.487	140.020	40.357	36.689	9.274
Bandwidth	413.600	326.442	261.460	270.705	271.802	351.041
Effective Obs	336277	270454	219451	226782	227648	289823
Panel B: Effect of additional representation of marginalized groups						
	Outcomes		Attendance			
	Total focus areas	Topics covered	Total	Women	SC	ST
RD_Estimate	0.0573	0.0228	4.7808	-1.2256	1.0297	-0.5032
	(0.0842)	(0.0171)	(7.0254)	(2.2730)	(1.8843)	(0.8914)
	[0.496]	[0.182]	[0.496]	[0.590]	[0.585]	[0.572]
Dep var mean	2.860	5.460	202.629	61.299	55.171	11.520
Bandwidth	0.017	0.015	0.012	0.022	0.015	0.030
Effective Obs	185581	155430	130759	230281	161465	308434

Note: This table reports regression discontinuity estimates of the effects of hyperlocal representation on Gram Panchayat Development Plan meetings. Panel A reports effects of increases in the number of ward members, and Panel B reports effects of increases in Scheduled Caste (SC) representation. Columns (1) examines effects on the total number of major topics covered at the meetings (out of 7), while Appendix Table A11 shows effects on each of the topics individually. Column 2 looks at the total number of development priorities set for the upcoming year. Columns (3) to (6) measure attendance at the meetings for all persons, women, scheduled castes, and scheduled tribes respectively. Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Gram Panchayat Development Plan Meeting Topics Covered

	Poverty issues	Current funds	Future resources	Mission Antyod.	MA gaps	GPDP passed	COVID-19
Panel A: Effect of additional political representatives							
RD_Estimate	0.0004	-0.0042	-0.0005	-0.0001	0.0030	-0.0001	-0.0012
	(0.0048)	(0.0032)	(0.0020)	(0.0029)	(0.0028)	(0.0012)	(0.0033)
	[0.940]	[0.200]	[0.822]	[0.964]	[0.290]	[0.939]	[0.723]
Dep var mean	0.378	0.880	0.953	0.851	0.871	0.981	0.932
Bandwidth	247.982	239.930	337.404	485.066	365.085	377.726	303.898
Effective Obs	208012	201802	278979	388575	300070	309139	156774
Panel B: Effect of additional representation of marginalized groups							
	Poverty issues	Current funds	Future resources	Mission Antyod.	MA gaps	GPDP passed	COVID-19
RD_Estimate	0.0093*	0.0029	-0.0001	0.0060	0.0026	0.0026	-0.0015
	(0.0052)	(0.0035)	(0.0030)	(0.0050)	(0.0038)	(0.0019)	(0.0050)
	[0.075]	[0.407]	[0.964]	[0.230]	[0.490]	[0.191]	[0.760]
Dep var mean	0.344	0.885	0.952	0.847	0.875	0.977	0.917
Bandwidth	0.018	0.016	0.015	0.014	0.014	0.018	0.013
Effective Obs	196981	166839	157651	146314	151399	197342	89908

Note: This table reports regression discontinuity estimates of the effects of hyperlocal representation on the topics discussed at Gram Panchayat Development Plan meetings. Panel A reports effects of increases in the number of ward members, and Panel B reports effects of increases in Scheduled Caste (SC) representation. The topics discussed are: (1) Presentation by self-help group members on poverty issues and poverty reduction plans; (2) Review of current year spending of local government funds; (3) Discussion on resources and plans for next year; (4) Presentation and validation of the data collected by the most recent round of the Mission Antyodaya initiative (see section B.1.2); (5) Discussion of the gaps revelead by the Mission Antyodaya data and proposals to fill those gaps; (6) whether the meeting passed a resolution on the GPDP priorities for the following year); and (7) Discussion of COVID-19 appropriate behavior (in 2020, 2021, 2022). Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Pivotality and Electoral outcomes

	(1) Total ward pop.	(2) Margin of victory	(3) Turnout
RD_Estimate	-25.106***	-4.260***	-0.797
	(2.70)	(0.99)	(0.80)
	[0.000]	[0.000]	[0.317]
Dep var mean	142.342	21.538	72.901
Bandwidth	206.640	234.719	169.205
Effective Obs	23737	24934	19672

Note: This table tests whether voters value hyperlocal representatives using turnout as a revealed-preference measure. Estimates are from regression discontinuity designs based on population thresholds that determine ward size in the 2021 ward member elections in Uttar Pradesh. Columns (1) and (2) show that adding a ward member reduces the number of eligible voters per ward and the margin of victory, increasing the probability that an individual voter is pivotal. Column (4) shows no corresponding increase in voter turnout. Within standard turnout models, this null response implies that voters place little instrumental value on these representatives. Robust standard errors in parentheses; p-values in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Supplemental details and analysis

B.1 Data appendix

This appendix provides additional details on the construction of each of the main datasets used in the paper, including issues related to data collection and matching for specific states.

B.1.1 Census and Local Government Directory

We use data from the Local Government Directory (LGD) and the Census of India to construct population measures and characteristics of gram panchayats. The LGD is a centralized administrative registry maintained by the Ministry of Panchayati Raj that assigns unique codes to local government entities and tracks their names, boundaries, and component villages. It also provides a standardized mapping of gram panchayats to higher administrative units-including blocks, districts, and states-and has become the backbone for linking administrative datasets collected by different ministries.

Population and demographic characteristics are drawn from the 2001 and 2011 Censuses of India, which provide decennial, village-level data on total population (including by broad caste category) and other characteristics, such as the presence of infrastructure. We link Census villages to gram panchayats using the LGD, which contains census codes for component villages. Villages are then aggregated to their corresponding gram panchayats using the Local Government Directory (Ministry of the Panchayat Raj, 2020) to construct the regression discontinuity running variables, including total gram panchayat population and the fraction belonging to Scheduled Castes. Census 2011 data are used for all states except Tamil Nadu, where the running variables are based on Census 2001 data.

B.1.2 Mission Antyodaya

The Mission Antyodaya initiative provides village-level administrative data on the delivery of individual public benefits across rural India. Launched by the Government of India, these data were collected by the central government in fiscal years 2019–20 and 2022–23 to provide inter-census snapshots of rural demographics, infrastructure, services, and welfare coverage. Mission Antyodaya indicators are drawn primarily from departmental administrative records rather than household surveys; for example, information on Below Poverty Line (BPL) ration cards is sourced from the Department of Food and Civil Supplies. The data are reported by local officials using standardized templates and subsequently validated and aggregated at higher administrative levels. As a result, Mission Antyodaya provides comprehensive and nationally comparable measures of program coverage.

Our analysis follows Narasimhan and Weaver (2024) in examining beneficiary counts for eight major welfare programs: (1) zero-balance bank accounts under the Jan Dhan initiative; (2) Below Poverty Line (BPL) ration cards providing access to subsidized food grains; (3) liquefied petroleum gas (LPG) connections under the Pradhan Mantri Ujjwala scheme; (4) pensions for the elderly, widows, and the disabled under the National Social Assistance Programme; (5) household electricity connections under the Saubhagya scheme (Pradhan Mantri Sahaj Bijli Har Ghar Yojana); (6) a Rs. 5000 cash transfer for pregnant women and mothers under the Pradhan Mantri Matru Vandana Yojana; (7) housing subsidies or waitlist

status under the Pradhan Mantri Awaas Yojana or related state schemes; and (8) access to publicly provided piped water under the Jal Jeevan Mission.

B.1.3 National Rural Employment Guarantee Scheme work records

We obtain annual, gram panchayat–level administrative data on the implementation of the National Rural Employment Guarantee Scheme from the Ministry of Rural Development for the period 2016 to 2023. These data are drawn from the official NREGS Management Information System and include information on project completion, person-days of employment generated, wage disbursements, and expenditures on labor and materials, among other outcomes. We downloaded the data between May and July 2024. Data for Telangana are not observed, as they were not available at the time of download and have since been removed from the system. For this reason, Table A3 reports match rates excluding Telangana.

B.1.4 National Rural Employment Guarantee Scheme work location records (Gram Manchitra)

The Gram Manchitra portal is a web-based geographic information system (GIS) platform developed by the National Informatics Centre under the Ministry of Panchayati Raj. The portal integrates multiple geospatial datasets to provide a unified view of village infrastructure. A key feature of the platform is the tracking of geo-tagged development works across schemes, including NREGS projects. Through integration with mobile data capture tools, assets constructed under government programs are mapped with GPS coordinates and photographs at multiple stages of implementation (before, during, and after work). These geo-referenced project points are displayed on Gram Manchitra's interactive map interface. For our analysis, the Gram Manchitra data provide a location-specific record of completed NREGS projects across states, allowing us to construct measures of spatial dispersion and equity in project placement within a gram panchayat.

We acquired the full Gram Manchitra data for sample states in September 2025, containing the GPS locations of 21 million completed NREGS projects between 2016 and 2023. A comparison with other NREGS administrative data indicates that this represents approximately 53.0 percent of all completed NREGS projects in the sample states over this period. The Gram Manchitra data do not include unique project identifiers that would allow project-level matching to other NREGS datasets, and we therefore cannot directly observe which types of projects are geo-tagged. However, it is unlikely that missing geo-tagged data are systematically related to the number of ward councilors, as shown in Appendix Table A3.[9]

B.1.5 Social Audits

We use data from NREGS social audits conducted between 2016 and 2024 across all states of India. These data were downloaded from the NREGS social audits website between Novem-

[9]Columns (3) to (5) of Appendix Table A3 examine whether the running variables predict the presence of any geo-located data for a given gram panchayat. We also test whether the discontinuity is related to the fraction of completed projects with geo-coded data, calculated by comparing the number of geo-tagged projects in Gram Manchitra to the total number of completed projects reported in the other NREGS data. We find no statistically significant relationship for either design (b = 0.0030, se = 0.0091, p = 0.745; b = 0.0057, se = 0.0092, p = 0.539).

ber and December 2025. NREGS social audits are a large-scale, citizen-led monitoring mechanism designed to improve accountability in program implementation. Audits are conducted by lightly trained lay auditors, primarily women affiliated with government-organized self-help groups, who are deployed to gram panchayats outside their home areas to reduce local capture. Audit teams typically spend approximately one week in each gram panchayat verifying whether beneficiaries listed in official records exist and actually worked, whether wages were paid as recorded, whether assets were constructed, and whether procedural rules were followed. The audit process culminates in a public meeting (gram sabha), where findings are presented to citizens, local implementers, and elected officials, and grievances are publicly discussed. Final audit reports are submitted to the state Social Audit Unit, digitized, and used to track issue resolution and, in some cases, trigger administrative action.

Experimental evidence from Bihar shows that social audits are effective at detecting implementation irregularities and can meaningfully alter subsequent program behavior, particularly for violations that are easily observable by citizens, such as non-payment for work or beneficiary-level kickbacks (Pande et al., 2025). In our context, social audit data therefore provide a program-specific and policy-relevant measure of monitoring and governance quality that captures forms of misconduct that hyperlocal representatives could plausibly observe and raise with higher-level authorities.

B.1.6 Financial audits

For most gram panchayats across India, financial audits are conducted annually by the Ministry of Panchayati Raj. We use audit data for fiscal years 2020–2022, downloaded from the Ministry's website in May 2024. Appendix B.3 documents a strong relationship between violations detected in these financial audits and findings from NREGS social audits. Because NREGS social audit results have been independently validated using household survey data in prior work (e.g., Pande et al., 2025), this correspondence suggests that the financial audits also contain a meaningful signal component.

Financial audits are conducted annually by state Local Fund Audit departments or equivalent authorities, operating under standards and procedures issued by the Comptroller and Auditor General of India (Comptroller and Auditor General of India, 2011). The objective of the audit is to assess whether gram panchayat accounts are free from material misstatement due to fraud or error. Auditors examine annual receipt and payment accounts and supporting records maintained under the Model Accounting System for Panchayati Raj Institutions, including cash books, bank reconciliation statements, vouchers, muster rolls, asset registers, and inventory records. The audit process places particular emphasis on areas prone to misappropriation, such as procurement, grants, labor payments, and works execution.

Audit teams consist of professionally trained, district-level officials who conduct record-based verification, supplemented when necessary by physical inspection of works and assets. Detected issues are classified into 19 standardized categories of irregularities, including procedural violations, non-production of records, and financial misappropriation. Findings are compiled into inspection reports and submitted to higher administrative authorities, where they may trigger corrective actions, recovery proceedings, or disciplinary measures. In our setting, the financial audit data provide a professionally generated measure of fiscal compliance and gram panchayat governance quality that complements social audits by capturing forms of misconduct that are less visible to citizens but central to accountability.

Table A13: Summary of Data Sources on Ward Members

Dataset	Coverage	Key Variables	Strengths	Limitations
State Election Commission	Uttar Pradesh, West Bengal	Age, Gender, Caste, Name; Education and Turnout (UP only)	Complete rosters of elected ward members; Contains electoral outcomes	Only available for two states
Gram Manchitra	All-India	Age, Gender, Caste, Name, Term start and end date	Relatively complete rosters for observed GPs	Missing rosters for many GPs
eGramSwaraj	All-India	Name, Gender	Coverage of most GPs across India	Rosters are frequently incomplete
Mahaegram	Maharashtra	Name, Term start and end date	Better coverage for Maharashtra than other data	Only for one state, rosters are frequently incomplete

B.1.7 Ward members

There is no exhaustive roster of ward members across India, so we combine information from five data sources of varying quality and detail. The first two sources are election data from the State Election Commissions of Uttar Pradesh and West Bengal, which provide information on ward members elected in the most recent gram panchayat elections. Two additional sources come from independent initiatives within the Ministry of Panchayati Raj: the Gram Manchitra mapping platform and the eGramSwaraj database, a gram panchayat–level accounting system that also reports ward member names and gender. While these two databases are intended to cover all of India, coverage is incomplete for some gram panchayats. The final source, the Mahaegram initiative, provides current ward member rosters for the state of Maharashtra.

Table A13 summarizes these data sources and their respective strengths and limitations. The primary challenge across all sources is incomplete coverage, either because data are missing entirely for some gram panchayats or because rosters do not include the full set of ward members (for example, reporting data for three members when population thresholds imply eleven). In addition, the latter two sources do not report ward member caste, which limits their usefulness for verifying the first stage in the second research design.

When a gram panchayat (GP) appears in multiple sources, we retain the source with the most complete roster. To calculate the total number of ward members in a GP, we select the roster that contains the largest number of ward members, conditional on observing at least five members.[10] For the sample states, the retained data source is Gram Manchitra for

[10]We estimate the first-stage relationship between the running variable and the number of ward members using GPs for which we observe at least five members, as rosters are likely to be incomplete below this

68,647 GPs, eGramSwaraj for 41,272 GPs, one of the State Election Commissions for 37,925 GPs, and Mahaegram for 4,509 GPs.

For estimating ward member demographics in Section 2, we prioritize the source with the most detailed information, ranking sources as follows: State Election Commissions, Gram Manchitra, eGramSwaraj, and Mahaegram. We do not impose a minimum roster size restriction for this exercise. This procedure yields an all-India dataset in which the primary data source is the State Election Commissions for 54,942 GPs, Gram Manchitra for 74,585 GPs, eGramSwaraj for 69,577 GPs, and Mahaegram for 11,129 GPs. The resulting data cover 2.07 million unique ward members across 210,233 GPs, representing 78 percent of all GPs in India. Gender is observed for 95.5 percent of members, caste and education for 69.0 percent, and age for 28.6 percent.

Reflecting reservation policies, women constitute 50.8 percent of ward members. Caste composition is broad-based, with 24.6 percent general caste, 39.3 percent Other Backward Classes, 23.4 percent Scheduled Castes, and 12.7 percent Scheduled Tribes. Ward members are typically middle-aged, with a median age of 40 (10th to 90th percentiles: 26 to 58), and have low levels of formal education: 41.2 percent are illiterate or have less than primary schooling, while only 2.2 percent hold a college degree or higher. Overall, these data indicate that ward members are demographically representative of marginalized groups, although limited formal education may constrain their capacity.

To estimate the total number of ward members nationwide, we assume that the average number of ward members per gram panchayat is similar in the 22 percent of GPs for which roster data are unavailable. This implies a total of approximately 2.63 million ward members in India. Other large countries with comparable hyperlocal elected bodies include China, Indonesia, and the Philippines. China has approximately 650,000 village committees, typically comprising three to seven members, implying between 1.9 and 4.4 million council members. Indonesia has 74,961 desa with five to nine members each, implying between 0.37 and 0.67 million members. The Philippines has approximately 42,000 barangays with about seven councilors each, implying roughly 0.3 million barangay councilors. Even taking conservative estimates, these four countries alone account for at least 5.2 million hyperlocal representatives, suggesting that the global total is likely substantially larger.

B.1.8 Gram Panchayat Development Plan meetings

To assess whether ward members play a meaningful role in shaping local government deliberative processes, we use data from the Ministry of Panchayati Raj on meetings convened to formulate annual Gram Panchayat Development Plans (GPDPs). In these meetings, citizens and elected representatives discuss and decide on development priorities for the upcoming year. Such meetings constitute an important channel through which citizens can influence local government decisions and public goods provision (Rao and Sanyal, 2010; Ban et al., 2012; Das, 2015). For example, Das (2015) estimates that a one standard deviation increase in the relative attendance of women compared to men at a gram sabha increases the provision of sanitation and health facilities by 0.5 and 0.6 standard deviations, respectively. We observe five years of GPDP data from 2018 to 2022, covering 1.2 million meetings across

threshold. The estimated relationship is similar without this restriction (estimate of 1.30 [se = 0.095] instead of 1.39 [se = 0.087]), but somewhat smaller, likely due to increased measurement error from including GPs with missing roster data.

264,834 unique gram panchayats (including 744,711 meetings in our sample states).

These data record attendance at each meeting, with additional detail on the number of attendees from traditionally disadvantaged groups, including Scheduled Castes, Scheduled Tribes, and women. The data also indicate whether meetings discussed a set of topics designated as priorities for the GPDP process: (1) presentation and validation of data collected under the most recent Mission Antyodaya initiative (see Section B.1.2); (2) discussion of gaps identified by the Mission Antyodaya data and proposals to address them; (3) presentations by self-help group members on poverty-related issues and poverty reduction plans; (4) review of current-year local government expenditures; (5) discussion of resources and plans for the following year; (6) discussion of COVID-19 appropriate behavior (in 2020, 2021, and 2022); and (7) passage of a resolution on GPDP priorities for the subsequent year. In addition, for the years 2020 to 2022, we observe the sectoral focus areas prioritized in the GPDP for the following year (e.g. Roads, Sanitation), which we analyze in Test 6 in Section 4.4.

B.1.9 Additional details on matching

Details on matching success rates are reported in Table A3. Match rates are high for most datasets across both panels, with 11 of 18 exceeding 95 percent and 16 of 18 exceeding 90 percent. The two cases with lower match rates correspond to the NREGS social audit data, with match rates of 86.3% in Panel A and 81.0% in Panel B within the sample bandwidth. These lower rates arise because social audits have not been fully rolled out in a small number of states, rather than due to difficulties matching records across datasets. Among gram panchayats where social audits were conducted, the match rate exceeds 98 percent.[11] Importantly, we find no systematic relationship between the discontinuities we study and the probability of matching, indicating that whether a gram panchayat receives a social audit is unrelated to the number or caste composition of its ward members.[12]

B.2 Fuzzy RD Analysis

Section 3 shows that while the first-stage relationships are strong, their magnitudes indicate incomplete compliance with the underlying institutional rules. For example, the coefficient on the number of Scheduled Caste (SC) representatives is not equal to one, even though an additional seat should be reserved for and filled by an SC representative. This could reflect imperfect compliance by state election commissions, cases in which a seat is reserved but no candidate stands for office, or incomplete data on ward members (for example, if some members are not recorded). Given these complications, we present the reduced-form RD relationships in the main text, which provide interpretable intent-to-treat effects.

An alternative approach would be to estimate a fuzzy RD design using the discontinuities as an instrument for the number or identity of ward members. A key challenge with this approach is that administrative data on ward members are incomplete for many gram panchayats across states and years. A standard fuzzy RD would therefore require restricting the sample to gram panchayats with complete ward member data, reducing sample size and

[11] States in our sample where fewer than 75 percent of gram panchayats have conducted social audits include Chhattisgarh (53%), Haryana (60%), Madhya Pradesh (38%), Odisha (25%), and West Bengal (50%).

[12] While NREGS and NREGS (location) have an associated p-value of 0.065 and 0.086 in Panel B, this is consistent with chance given the number of regressions run.

precision. Instead, we implement a fuzzy RD design using an RD analogue of two-sample instrumental variables (Angrist and Krueger, 1992, 1994; Inoue and Solon, 2010), in which the outcome and treatment discontinuities are estimated separately and then combined using a local Wald estimator (Hahn et al., 2001). Intuitively, this approach rescales the reduced-form RD estimates in Table 2 by the corresponding first-stage estimates in Table 1. Appendix Tables A14 and A15 report the resulting estimates. Because the first stage is very strong, these estimates are effectively rescaled versions of the reduced-form results and do not alter the substantive conclusions of the paper.

Table A14: Fuzzy RD for density of representation

	(1) Workfare index	(2) Workfare project dispersion	(3) Benefit programs index	(4) Audit violations	(5) Social audit violations
Fuzzy RD	-0.009	-0.036	0.014	0.026	-0.039
	(0.010)	(0.022)	(0.010)	(0.028)	(0.070)
	[0.393]	[0.109]	[0.141]	[0.354]	[0.582]
Dep var mean	-0.126	1.407	0.012	1.925	4.877
Effective Obs (RF)	268125	292777	116978	542027	156257
Effective Obs (FS)	25060	25060	25060	25060	25060
First-stage F	252.60	252.60	252.60	252.60	252.60

Note: This table reports fuzzy regression discontinuity estimates of the effects of additional hyperlocal representation on main governance outcomes. We report a Wald estimator of the ratio of the reduced form and first stage estimates. Outcomes are the same as in table 2. All outcomes are measured at the gram panchayat level and standardized where indicated. Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Table notes report the relevant first stage F-statistic as well as the effective sample size for the reduced form RD and first stage RD. Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Fuzzy RD for density of representation

	(1) Workfare index	(2) Workfare project dispersion	(3) Benefit programs index	(4) Audit violations	(5) Social audit violations
Fuzzy RD	-0.033	-0.077	0.019	-0.214	0.086
	(0.041)	(0.072)	(0.040)	(0.163)	(0.170)
	[0.424]	[0.283]	[0.636]	[0.190]	[0.611]
Dep var mean	-0.147	1.437	-0.016	2.207	3.865
Effective Obs (RF)	291012	245623	77303	471845	121463
Effective Obs (FS)	49668	49668	49668	49668	49668
First-stage F	63.31	63.31	63.31	63.31	63.31

Note: This table reports fuzzy regression discontinuity estimates of the effects of additional hyperlocal representation on main governance outcomes. We report a Wald estimator of the ratio of the reduced form and first stage estimates. Outcomes are the same as in table 2. All outcomes are measured at the gram panchayat level and standardized where indicated. Estimates use local linear RD with triangular kernels and MSE-optimal bandwidths (Calonico et al., 2014, 2018). Table notes report the relevant first stage F-statistic as well as the effective sample size for the reduced form RD and first stage RD. Standard errors are clustered at the GP level (parentheses); p-values are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Cross-check of the audits data

Section 4.3 uses two data sources to measure monitoring and corruption. The first is financial audits conducted by the Ministry of Panchayati Raj, which review gram panchayat finances and are carried out by professional, district-level audit teams. The second consists of NREGS social audits, in which trained lay auditors from outside the village inspect recent works and interview residents to verify payments. While the financial audit data are novel, prior work shows that NREGS social audits are effective at detecting and deterring corruption (Pande et al., 2025).

To assess the informational content of these audits, we examine whether gram panchayats with higher detected violations in one system also exhibit higher violations in the other. Although the audits cover different functions and need not be strongly correlated, a positive relationship would indicate that both capture underlying governance quality and corruption. Using three years of overlapping data, Columns (1) and (2) of Appendix Table A16 regress financial audit violations on social audit violations in the same year, clustering standard errors at the gram panchayat level. Column (1) includes block and year fixed effects, while Column (2) includes gram panchayat and year fixed effects. The latter specification is particularly stringent, as it exploits within-gram panchayat variation to test whether years with more social audit violations also exhibit more financial audit violations. In both specifications, the estimated relationship is highly statistically significant, with t-statistics of 12.4 and 12.0.

Columns (3) and (4) repeat the analysis for violations closely linked to corruption. In financial audits, these include "Variation in accounts," "Irregularities," and "Non-production of records," while in the social audits they include violations labeled "Financial misappropriation" and "Financial deviations." We again find a strong positive relationship across the two audit systems, with t-statistics of 10.2 and 6.6 respectively. Together, these results suggest that both audit systems capture meaningful variation in GP governance quality.

Table A16: Relationship between detected financial and NREGS audit violations

	(1) Violations (finan.)	(2) Violations (finan.)	(3) Corruption (finan.)	(4) Corruption (finan.)
Violations (NREGS)	0.0402***	0.0550***	–	–
	(0.0033)	(0.0046)		
Corruption (NREGS)	–	–	0.0095***	0.0076***
			(0.0009)	(0.0012)
Block FEs	Yes	No	Yes	No
GP FEs	No	Yes	No	Yes
Year FEs	Yes	Yes	Yes	Yes
Dep var mean	3.0676	3.0986	0.7107	0.6759
Observations	187,330	137,417	187,330	137,417

Note: This table reports a regression of violations detected in the financial audits data on violations detected in the NREGS social audits data. The sample is from the years 2021-2023, with one observation for each GP and year in which there are audits from both data sets. Columns (1) and (2) report the total violations detected in each dataset, while columns (3) and (4) focus on violations more closely tied to corruption. Columns (1) and (3) include block fixed effects, while columns (2) and (4) include GP fixed effects. All columns include year fixed effects Standard errors are clustered at the GP level (parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$