

Learning to Govern: The Impact of Politicians' Peer Networks*

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Abstract

Many elected leaders enter office with limited knowledge of how government works and must learn to govern on the job. We examine whether peer networks of local politicians can facilitate such learning and improve governance. In a large-scale field experiment involving over 7,500 elected village councillors in Bihar, India, we randomly assign politicians to cross-village peer groups that regularly discuss governance challenges. Peer groups raise politicians' knowledge of governance processes and best practices. We identify substantial knowledge spillovers to untreated political colleagues, particularly when councillors share a caste, religious or partisan identity, and for non-rivalrous schemes. Peer groups also increase politicians' confidence and agency, and expand their professional and party networks while modestly increasing conflict within the village. Treated villages prepare more effective development plans, and increase expenditure on public goods that citizens prioritise and councillors campaigned on. Our findings demonstrate that peer networks build politicians' capacity and diffuse knowledge across local governments.

Keywords: peer learning, politicians, local governance

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1 Introduction

Elected leaders are tasked with translating citizens' priorities into concrete plans and policies. Politicians listen to citizens' concerns and then work within government—alongside bureaucrats and other elected representatives—to address them. To be effective, politicians need to understand how government works. However, due to turnover and term limits, many leaders enter office without a firm grasp of formal government procedures or the tacit know-how required to navigate the state and get things done. Politicians must therefore learn to govern on the job. Supporting on-the-job learning could improve governance, and will become more important as efforts to broaden representation and decentralise power bring fresh leaders into office ([Chattopadhyay and Duflo, 2004](#)). Despite this, there is limited evidence on how to facilitate politicians' learning.

In other contexts, peer interactions play a key role in enabling on-the-job learning. Farmers adopt new technologies in part by observing their peers ([Foster and Rosenzweig, 1995](#); [Beaman et al., 2021](#)). Managers learn about business opportunities and best practices through professional networks ([Cai and Szeidl, 2018](#)). Students absorb knowledge and attitudes from their classmates and roommates ([Duflo et al., 2011](#); [Sacerdote, 2011](#); [Corno et al., 2022](#); [Zárate, 2023](#); [Chen and Hu, 2024](#)), and employees acquire skills from their colleagues ([Sandvik et al., 2020](#)). Similarly, fellow politicians may be an excellent source of knowledge about government processes and have valuable contacts and practical strategies to overcome common challenges—the “hidden curriculum” required to govern well.¹ Yet we know little about whether peer interactions can facilitate politicians' learning and improve governance.

In this paper, we examine the impacts of fostering peer networks among politicians. We conduct a large-scale field experiment with local elected leaders in Bihar, India's poorest state, whose 105 million residents constitute 2% of the global population living in a democracy. Partnering with the Rural Development Department, we convene peer groups for ward members (WMs), the lowest tier of elected representatives in rural India. Each WM represents about 1000 citizens and serves on the governing council of their Gram Panchayat (GP), the smallest unit of rural government, where they formulate and oversee village development plans.² WMs are the largest single group of elected representatives globally: with more than 100,000 in Bihar alone and over two million across In-

¹Many countries maintain associations or forums for local leaders to exchange such information and coordinate action. Examples include the U.S. Conference of Mayors, the Association of Local Authorities of Mexico, and the National Front of Mayors (FNP) in Brazil. FNP's annual convention enabled [Hjort et al. \(2021\)](#) to evaluate the impact of disseminating information on policy effectiveness to mayors.

²GPs typically consist of 4-5 villages and are governed by an elected council comprising 12-14 ward members and a directly elected president.

dia, even modest gains in their capacity could meaningfully improve governance at scale ([Narasimhan and Weaver, 2026](#)).

Our setting provides an excellent laboratory to evaluate the potential of peer learning. Most WMs are first-time elected officials with limited knowledge of their own role: the median WM knows only 40% of the steps required to implement the schemes under their purview. But there is significant variation: bottom-decile WMs identify none of the required steps, while top-decile WMs identify about 60%. In addition, WMs operate within a common bureaucracy, interact with the same block- and district-level officials, while individual WMs often have knowledge of particular schemes or governance tasks that others lack, creating scope for peer learning. Peer WMs are thus a rich source of procedural and strategic information. Nevertheless, peer networks among WMs were rare: at baseline, 82% did not discuss work with any WM outside their GP.

We invited randomly selected WMs to join a peer group of 10-12 WMs from their district. Over the next 18 months, each group met twice in person, held quarterly conference calls, and communicated through their own WhatsApp group. Trained moderators facilitated these interactions but offered no governance information themselves. To estimate both direct and spillover effects, we randomised in stages: we first selected GPs for treatment, then invited 2-4 randomly chosen WMs within each treated GP, and finally randomly assigned invitees from each GP to different peer groups. We identify direct effects by comparing invited WMs ("treated WMs") with WMs in control GPs ("control WMs"), and capture within-GP spillovers by comparing non-invited WMs in treated GPs ("spillover WMs") against control WMs. The experiment was conducted at significant scale ([Muralidharan and Niehaus, 2017](#)): 2,424 treated WMs participated in 206 peer groups, and our sample of 7,719 WMs spans 2,213 GPs—968 treated and 1,245 control—collectively responsible for over 27 million citizens, a quarter of rural Bihar.

Participation in the peer groups was high: average attendance across the two in-person meetings and four calls exceeded 70%. The intervention was effective at fostering cross-GP connections: at endline, treated WMs were 51 percentage points more likely than control WMs to report knowing a randomly selected member of their assigned peer group (control WMs were assigned to fictitious groups that never met). Leveraging rich data on the content of group discussions, we document that the groups exchanged useful information, sharing nearly 19 governance best practices—concrete solutions to common challenges—across their interactions.

We find that peer networks facilitated learning. We measure four different types of governance knowledge: formal knowledge of required procedural steps; tacit knowledge of informal practices; procedural knowledge based on scheme-specific factual questions; and

best-practice knowledge for addressing implementation problems. Aggregating across these measures, we find that treatment increases WMs' knowledge by 0.13 standard deviations (SD), driven primarily by gains in tacit knowledge and knowledge of governance best practices. Control WMs' knowledge also increased after 18 months in office: on average, they knew 5.5pp more steps required to implement schemes under their charge. Treated WMs identify 10.3pp more steps than at baseline, indicating that peer groups nearly double politicians' rate of on-the-job learning.

These learning gains spill over to non-invited WMs in treated GPs. Spillover WMs experience a 0.08 SD increase in knowledge, nearly two-thirds of the direct treatment effect. Since each GP has 2-4 treated and 10 spillover WMs, these within-GP spillovers account for a large share—perhaps 60-75%—of the total knowledge gain due to the intervention.

We find that group identity and strategic considerations influence the diffusion of knowledge within GPs. Untreated WMs who share a caste, religious or partisan identity with their treated GP colleagues experience greater knowledge gains. Spillovers also differ sharply across schemes: they are concentrated in non-rivalrous schemes but are absent for rivalrous schemes, where better access in one ward may reduce availability in another, echoing patterns in other settings ([Cai and Szeidl, 2018](#)). By contrast, treated WMs learn a similar amount about rivalrous and non-rivalrous schemes, reflecting the fact that peer groups comprise WMs from different GPs who generally do not compete for the same resources. Taken together, our findings suggest two channels for learning. Treatment fosters ties with other WMs who share knowledge. This learning flows to untreated WMs within the GP, with social and strategic considerations shaping what information is shared.

Beyond facilitating learning, peer groups also increase WMs' agency. Treated WMs report 0.09 SD greater confidence in implementing schemes under their charge. They also exhibit greater collective efficacy: in a cross-randomized sub-experiment, treated WMs are 40% more likely to garner support for a petition requesting more autonomy and responsibilities for WMs. In a context where elected leaders often intermeddle on behalf of citizens to remedy service delivery failures, this greater agency has the potential to improve governance. In a second sub-experiment, however, we find a limited average effect on complaints lodged via Bihar's grievance redressal system, though we attribute this to very low overall take-up and frictions in using the scheme ([Sharan and Kumar, 2025](#)).

The intervention also expanded WMs' professional networks. Treated WMs know more WMs outside their GP, are more likely to confer with block-level bureaucrats responsible for implementing development projects, and are more likely to be involved with political parties. These networks also grow organically for control WMs, but expand faster for treated WMs. Combining peer, bureaucratic and political networks into an index, we find

that peer groups expand professional networks by 0.15 SD. However, improved agency and stronger professional networks are accompanied by greater friction within the GP. Treated WMs report worse relationships and more conflict with the powerful GP head and village-level officials, and participate less frequently in *Gram Sabha* (village council) meetings. This friction is significant because the GP head plays an important role in local governance and can exercise hold-up power over development projects (Sharan and Kumar, 2025).

We examine how peer groups affect local economic development by studying Gram Panchayat Development Plans (GPDP), the annual process through which GPs plan development projects and allocate public resources. *Ex ante*, the effect of our intervention on these downstream outcomes is ambiguous. Greater knowledge, agency, and external networks may strengthen WMs' ability to influence local planning, while increased conflict and reduced participation within the GP may impede coordination. Using administrative data on all GPDP projects, we find that treated GPs develop more effective development plans. Reflecting WMs' improved capacity, treated GPs plan more ambitious projects, allocating 3% more spending to each scheme than control GPs. This additional spending is concentrated on local priorities—public goods that citizens value and WMs campaigned on. Treated GPs allocate 35% more to schemes receiving the greatest campaign support and 34% more to those receiving the greatest citizen demand, while effects are close to zero for schemes with little support. In treated GPs, WMs have more accurate beliefs about citizens' preferences, suggesting that improved knowledge of local priorities may play a role. GP development plans also improve most in electorally competitive GPs, highlighting an important role for political incentives. Although these are development plans rather than completed projects, an independent audit confirms that many of these plans moved into implementation: survey teams located 51% of a random sample of planned projects. Taken together, our findings illustrate that peer groups helped WMs perform better at their core responsibility—translating citizens' concerns into concrete government action.

Despite these improvements in development plans and activity, citizens do not perceive significantly improved access to public goods or welfare schemes, nor do they evaluate their WM more favourably. We find no evidence that these patterns reflect increased corruption: treated WMs do not engage in greater self-dealing of National Rural Employment Guarantee Scheme (NREGS) workfare payments, and citizens do not report paying higher bribes to access public services. The timing of the citizen survey and difficulties in attributing projects to WMs may instead help explain these findings. The survey was conducted while many GPDP projects were still in progress; more than half the projects located in our independent audit were completed after the citizen survey. Moreover, citi-

zens often attribute completed projects to the GP head or local bureaucrats rather than to their WM. Within-GP spillovers may also reduce citizens' ability to notice improvements in their WM's capacity. The absence of detectable political returns for WMs is consistent with delayed implementation, attribution frictions in collective choices, and substantial spillovers.

Finally we provide evidence that treatment effects are larger in groups that exchanged more information. Using detailed meeting records, we measure the richness of information exchange by the number of governance best practices shared within each group. Learning gains are concentrated in groups with above-median information exchange: WMs in these groups experience a 0.08 SD increase in knowledge, while those in below-median groups exhibit virtually no gain. Information exchange also appears to facilitate gains in WM agency: treated WMs in high information exchange groups are more confident and file more complaints via the grievance redressal system. These patterns suggest that learning and information diffusion mediate the effects of the intervention, but should be interpreted cautiously since information exchange is measured after treatment assignment.

We also examine who benefits from peer networks. Using the causal-forest method of [Wager and Athey \(2018\)](#), we find that predicted treatment effects on knowledge are positive for the vast majority of WMs. Yet WMs with greater higher baseline knowledge and education tend to benefit more. Thus, the intervention appeared to work best in settings with high pre-existing political capacity: more capable WMs learn more, spillovers are stronger in less ethnically fractionalised GPs, and development plans improve most in electorally competitive GPs, potentially widening inequalities among GPs.

Overall, our experiment demonstrates that peer networks can strengthen the capacity of local elected leaders, facilitate diffusion of governance knowledge through spillovers, and improve the allocation of public resources. Treated GPs plan more ambitiously and direct additional spending toward local priorities and WMs' campaign commitments. The intervention was highly cost-effective: back-of-the-envelope calculations suggest that each dollar spent generates approximately \$25.5 in planned public goods expenditure and \$13 in implemented public goods. Peer learning among politicians may therefore represent a scalable approach to improving governance in low-capacity environments.

Our paper contributes most directly to the literature on peer learning. Peers are an important source of knowledge about best practices in a variety of contexts, including agriculture ([Foster and Rosenzweig, 1995](#); [Conley and Udry, 2010](#); [Beaman et al., 2021](#)), education ([Sacerdote, 2011](#)), business ([Cai and Szeidl, 2018](#); [Fafchamps and Quinn, 2018](#); [Brooks et al., 2018](#); [Iacovone et al., 2022](#)), and the workplace ([Sandvik et al., 2020](#); [Papay et al., 2020](#)). There is, however, little research on peer learning among politicians, and

no evidence on whether it improves governance. Research on peer influence in politics is limited to a few studies that explore how social interactions between legislators in the US Congress and European parliaments affect legislative behaviour ([Harmon et al., 2019](#); [Canen et al., 2023](#); [Lowe and Jo, 2025](#); [Kumar et al., 2026](#)) and focus on alternative mechanisms such as social pressure and vote-trading.

Perhaps the closest paper to ours is [Cai and Szeidl \(2018\)](#), which found that assigning Chinese SME managers to peer groups improved firm profits and management practices. We study an analogous intervention in a very different setting—local politics in India—and show that peers facilitate on-the-job learning, strengthen elected leaders’ capacity, and improve governance. Going beyond [Cai and Szeidl \(2018\)](#), our experiment design and data allow us to identify substantial spillovers to untreated political colleagues and link information exchange within groups to learning. We also document how peer networks expand politicians’ agency and external ties while generating new frictions within the GP.

Second, we provide evidence on how to improve the performance of elected leaders. Existing work focuses on two margins: improving selection, by influencing who enters politics ([Gulzar and Khan, 2025](#); [Gulzar, 2021](#); [Dal Bó et al., 2024](#)) or is selected for public office ([Casey et al., 2021, 2026](#)); and improving politicians’ incentives, by empowering voters with information and strengthening electoral accountability ([Casey, 2015](#); [Avis et al., 2018](#); [Banerjee et al., 2024](#)). We study a third margin: improving politicians’ capacity to govern once in office. Taking selection and incentives as given, we show that peer networks help incumbents acquire the know-how required to govern more effectively. While prior work documents substantial gaps in elected leaders’ knowledge of government ([Auerbach et al., 2023](#)), and demonstrates the value of training in other contexts ([Anderson and McKenzie, 2022](#); [Campos et al., 2025](#)), there is limited evidence on how to build politicians’ capacity or whether doing so can improve governance.

Finally, we contribute to the literatures on decentralisation and policy diffusion. Decentralisation creates scope for local experimentation ([Wang and Yang, 2025](#); [Luo et al., 2025](#)), but its benefits may be limited when local politicians lack capacity ([Narasimhan and Weaver, 2026](#)). Prior work shows that policies diffuse through academic evidence ([Hjort et al., 2021](#)), geographic proximity, partisan alignment ([DellaVigna and Kim, 2022](#)), electoral considerations ([Bernecker et al., 2021](#); [Shigeoka and Watanabe, 2023](#)), and bureaucratic rotation ([Lu, 2023](#)). We identify politician networks as another channel, showing experimentally that local elected leaders learn governance practices from their peers. Peer networks can therefore complement decentralisation by helping to spread best practices across local governments.

The remainder of this paper is as follows: Section 2 describes the background of our experiment, section 3 describes the research design and our sub-experiments, section 4 describes the data sources, section 5 details our empirical specifications, section 6 discusses our main findings, section 7 describes the mediating role of information exchanged in meetings, section 8 describes the cost-benefit analysis and section 9 concludes.

2 Background

2.1 Local Government in India

Nearly 65% of Indians live in rural areas, where the smallest administrative unit is a GP. In Bihar, each GP consists of 3-4 villages, and is governed by an elected council, which is headed by a GP head (*Mukhiya*) and comprises on average 13.6 WMs. Groups of GPs (approximately 12-16) are organised into blocks, whose development activities are coordinated by the Block Development Officer (BDO), a key bureaucrat.

GPs are responsible for the local implementation of most rural development and anti-poverty programs, including programs devised and funded by the national and state governments. The vast majority of village public works and services are managed by the GP. Social protection schemes that provide employment, pensions and subsidised food and housing also rely on the GP to select beneficiaries. Thus, improving the quality of GP governance could strengthen social safety nets, improve public good provision and promote local economic development in rural India.

2.2 Role of Ward Members

Our study focuses on WMs, who comprise the lowest tier of politicians in India and each represent about 1,000 citizens. WMs play both formal and informal roles in delivering public services. According to the Bihar Panchayati Raj Act (2006), WMs are responsible for carrying out development activities in their wards. They have a formal role in implementing several public works programs, including schemes related to drains and lanes construction (*Nali Gali*), solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), and the provision of tap water (*Nal Jal*) and solar street lights.³ WMs are also formally in charge of identifying beneficiaries for several important social protection schemes, including subsidies for house construction (*Pradhan Mantri Awas Yojana*, PMAY)

³WM responsibilities for the tap water (*Nal Jal*) scheme have changed over time. Additional powers and responsibilities were given to WMs in 2016, while in May 2023, a cabinet order transferred some of the WM powers to the Public Health Engineering Department (PHED).

and subsidies for toilet construction (*Swacch Bharat Abhiyaan*, SBM) programs. Consistent with this broad remit, WMs report being primarily responsible for a range of public works and social protection schemes, although their reported responsibilities vary substantially across schemes (Appendix Table A1). They are also perceived by citizens as the primary contact for scheme-related help, particularly for the implementation of the tap water scheme (Appendix Table A2).

However, from qualitative interviews with citizens, we have learnt that WMs' roles extend beyond their formal responsibilities. As locally embedded leaders, WMs are often citizens' first point of contact with the state. We have observed that WMs help citizens apply for social welfare benefits like pensions (for which most elderly, widowed and infirm citizens are eligible), subsidised food rations (Public Distribution System, PDS), and work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA). A substantial share of citizens rely on the WM as their primary contact for these schemes: 19% for subsidised food rations (PDS), 28% for NREGA, and 33% for subsidized housing (PMAY) (Table A2).

Citizens also seek their WM's help to lodge complaints about local public goods (e.g., quality of roads) and services (e.g., absenteeism of the local childcare worker). These complaints are often expressed via petitions that WMs submit to local bureaucrats like the BDO.

Even for programs WMs formally manage, they must often negotiate with upper-level officials (like the GP head and BDO) to release funds for project implementation.⁴ Hence, a key aspect of a WM's job is to mediate between her constituents and the relevant upper-level officials who have *de facto* control of the allocation of public resources.

Thus, WMs serve as both implementers and representatives in our context. This dual function is common among local leaders in developing countries and may even be inherent to the role of politicians in representative government.

2.3 Relationship with the GP head

Unlike in some other Indian states, GP heads in Bihar are directly elected by the entire GP. Consequently, the GP head is not merely first among equals but holds significantly greater *de jure* authority than the WMs. This formal authority translates into substantial *de facto* power as well: WMs command only a small fraction of the financial resources available to the GP head and must rely on the GP head's approval to access additional funds for most

⁴Like many local politicians, WMs directly control only a small fraction of their GP's overall expenditure. Moreover, funds for many national and state government programs are only devolved to the block level to be administered by the BDO.

activities.

This institutional arrangement results in ongoing contestations over authority and resources between WMs and the GP head. In 2017, WMs were allocated direct funding to implement key water and sanitation infrastructure projects within their wards. GP heads, who had until then exercised control over virtually all Panchayat funds, resisted this policy change and went so far as to challenge it in court, demonstrating their unwillingness to cede financial authority to WMs.

Even after the courts ruled in favor of the WMs, [Sharan and Kumar \(2025\)](#) show that WMs often struggled to implement these projects effectively, in large part due to obstructive actions by GP heads. In many cases, GP heads withheld funds from WMs, a dynamic that was further exacerbated when the GP head and the WM belonged to different caste groups.

2.4 Scope for Peer Learning

Serving as a WM is often an entry point into politics. In our sample, 68% of WMs are first-time elected officials, and nearly all have no formal party ties because parties are officially barred from contesting GP elections in Bihar.⁵ As a result, most WMs lack both experience and systematic knowledge about how local governance works, including how to manage the development schemes under their charge (see Section 5).

First, while baseline knowledge is generally low, there is substantial variation across both schemes and WMs. On average, WMs correctly identify only about 38% of the steps required to implement schemes under their charge, with scheme-level averages ranging from roughly 10% for the tap water scheme to about 73% for subsidized food rations. There is also considerable dispersion across WMs: those in the bottom quartile know fewer than 28% of required steps, while those in the top quartile know about 51% (see Appendix Table A3). This heterogeneity creates substantial scope for peer learning, as WMs may possess different pieces of scheme-specific knowledge or practical experience navigating local bureaucracies, which can be shared through peer interactions.

Second, WMs in the same district operate within a common bureaucratic structure and interact with many of the same block- and district-level officials. Peer groups therefore allow WMs to share procedural knowledge, such as how forms should be filled, which officials handle specific tasks, and how to follow up on stalled projects. Our qualitative work and pilot meetings suggest that while individual WMs often lack this procedural

⁵This is true for Bihar and most Indian states. Some states, like Kerala and West Bengal, allow candidates to contest on party tickets in GP elections.

knowledge, they are able to piece it together collectively.⁶

Third, there is considerable scope for horizontal information-sharing among WMs on how to navigate interactions with the GP head, who wields significant authority within the GP. GP heads typically control the majority of financial resources at the GP level, maintain extensive networks with local elites, and act as gatekeepers of information related to policy rules and implementation. As a result, WMs may depend heavily on the GP head for information about what is possible and how to get things done. Interacting with peers from other GPs can therefore help WMs better understand their own relationship with the GP head, including alternative ways of negotiating, asserting their roles, and accessing resources.

Fourth, because a WM's role evolves as policies change, formal training can quickly become outdated. In this dynamic environment, it is valuable for WMs to discuss ongoing challenges with other leaders facing similar governance problems. For instance, when responsibilities over local water and sanitation infrastructure shifted away from WMs, peer interactions may have helped WMs understand how to exercise influence through alternative channels, including planning processes and engagement with higher-level officials.

Despite this potential, baseline data show that (non-GP) peer networks were severely limited: 82% of WMs reported that they did not know or discuss work with any WM outside their own GP. Taken together, these factors highlight why peer learning may be a promising strategy for enhancing governance capacity in this setting.⁷

3 Research Design

3.1 Overview of the Intervention

This paper aims to understand the value of expanding peer networks among elected politicians. Partnering with the Government of Bihar, we implemented a randomised control trial (RCT) where we organised peer groups for local politicians. We drew a representative sample of WMs from 10 districts, and randomly assigned WMs either to (i) treatment, (ii) a spillover sample or (iii) a control group. See Figure A1 for a visual description of the sample.

⁶WMs in our context are unlikely to see each other as competition. Most WMs (70%) are holding an elected office for the first time. While some WMs will subsequently contest elections for GP-level positions (e.g. GP head or Panchayat Samiti), very few will end up contesting higher-level political office. Hence, since WMs in a peer group are almost always from different GPs, they are very unlikely to ever compete directly against each other. Consistent with this, our observation of the dynamics of the group meetings suggest that WMs see themselves as peers rather than competitors.

⁷A related reason to study peer learning is that disadvantaged castes may particularly benefit from access to external peer networks; we examine this issue in a companion paper.

Each peer group consists of 10-12 WMs sampled from the same district.⁸ We organise regular interactions for treated politicians. Peer groups have (i) an introductory meeting for group members in the district headquarters; (ii) a second in-person meeting after 8-9 months; (iii) quarterly conference calls; (iv) a WhatsApp group chat that can be freely used to exchange information. In a context where most WMs do not know WMs outside their GP, our intervention aims to increase interactions between WMs and cultivate peer networks among them. In total, we organised 206 peer groups comprising 2,424 WMs.

Our moderators participate in these meetings, but only to structure the conversations. Participants are told that the objective of these meetings is for them to discuss issues relevant to their job as WMs, and they are encouraged to raise issues and offer solutions to problems they face. We make clear that moderators are not in a position to offer any suggestions.

Figure 1 summarizes the sequence of intervention activities and data collection over the course of the study, including peer-group meetings, conference calls, WhatsApp interactions, the embedded sub-experiments, and the baseline and endline surveys.

3.2 Sampling

District Sampling Our interventions runs across 10 districts of Bihar, which together account for 36% of the population of the state. These 10 were selected on the following criteria: (i) population and (ii) region. We pick the top 7 districts in terms of rural population⁹. The three additional districts increase representation of populations from the east¹⁰ and the south¹¹. Together, these 10 districts span 6 out of the 9 major divisions of Bihar.

GP & Ward Sampling Within districts, we followed a two-stage randomisation (See Figure A1), first sampling GPs and then wards.

GP Sampling: Within each district, we randomly drew 85% of GPs within a 55 KM radius of the district headquarters for the experiment. Over 90% of GPs lie within this distance.¹² Within these GPs, we randomly assigned 40% of GPs to treatment and the rest to control. Together, this gave us a total sample of 2213 GPs (see Table A4). Panel A of Figure A2 shows that our experimental GPs cover a large share of the sampled districts.

⁸A district has, on average, 211 GPs and 2842 WMs.

⁹These are: Purbi Champaran, Muzaffarpur, Madhubani, Gaya, Samastipur, Saran and Darbhanga.

¹⁰Purnia and Banka.

¹¹Jehanabad.

¹²The 55 KM radius was introduced because WMs found it very difficult to travel long distances to show up for the meeting. These remote GPs, which we exclude from the sample, tend to be poorer and larger. For the first district, Samastipur, we drew only 82% of GPs and had no distance threshold.

Ward Sampling: For 6 out of 10 districts, we randomly drew 2 treatment wards and 2 spillover wards for each treated GP and 2 control wards from each control GP to be enrolled in our experiment. For the final 4 districts, we increased the number of treatment and control wards to 4, while keeping the number of spillover wards to 2. Our final sample had 7719 wards, of which 2424 were treated, 3460 were control and 1835 were spillover wards (see Table A5).

SC WMs: We oversampled SC WMs — 32.8% of our sample are SC versus 20.6% in our sample districts. Like other WMs, SCs are randomised into treatment, spillover or control. However, in addition, treated SC WMs are randomly assigned either to SC-only groups or mixed groups, which contain both SC and non-SC WMs. Out of 206 groups, 36 were SC-only and these contained 53% of SC WMs.

Group Size: Groups have 12 members, except in Samastipur district, where groups had 10 members.

Overall, our experiment was designed in line with the principles of *experimentation at scale* (Muralidharan and Niehaus, 2017). Our sample was large — 7,719 WMs from 10 districts, covering 18% of WMs in these districts and 26% of GPs in Bihar; and representative of over 105,000 WMs in Bihar alone. We randomised at the GP level, to enable estimation of within-GP spillovers.¹³

3.3 Sub-Experiments

In addition to the main peer-network intervention, we implemented two embedded sub-experiments designed to measure whether participation in peer groups affects how politicians respond to governance challenges. The first examines whether WMs are better able to mobilise others around collective causes, while the second tests whether they are more willing to use formal institutional channels to address service-delivery problems. Both sub-experiments were conducted among randomly selected subsets of treatment and control WMs.

Collective Action. To measure politicians’ ability to mobilise others around governance issues, we implemented a collective-action sub-experiment. Approximately 790 randomly selected WMs were invited to organize a petition on one of two policy issues: (i) restoring WMs’ role in managing tap water (*Nal-Jal*) projects in their wards, or (ii) granting WMs greater autonomy in NREGA implementation. We subsequently tracked whether WMs collected any signatures, whether they collected signatures from other WMs, and the total number of signatures obtained.

¹³Panel B of Figure A2 plots one example group per district.

Grievance Redressal. To measure whether WMs use formal institutional channels to address governance problems, we implemented a grievance-redress sub-experiment. A randomly selected subset of treatment and control WMs received information about Bihar’s Grievance Redressal Scheme, which allows citizens to file complaints regarding service-delivery failures and requires the government to convene a hearing within 60 days. We subsequently tracked whether WMs filed a complaint under the scheme.

4 Data

4.1 Data Sources

Our analysis draws on five sources of data. The first two are a baseline survey ($N = 7,277$) and an endline survey ($N = 6,213$) of WMs which we conducted, collecting information on demographic characteristics, political experience, campaign priorities, governance activities, and professional relationships. Third, we collected detailed records of peer-group interactions, allowing us to measure the informational content of meetings and exposure to peer learning. Fourth, we use administrative data on local governance outcomes, including GPDP records and NREGA administrative data. Finally, we conducted a citizen survey to measure spending priorities, perceptions of local governance, and assessments of elected representatives.

Using these data, we construct two broad sets of outcomes: WM-level outcomes and downstream governance outcomes.¹⁴ WM-level outcomes include measures of knowledge, networks, and agency. Governance outcomes capture public spending priorities, programme implementation, and citizens’ preferences and perceptions of local governance. In addition, we use a rich set of baseline covariates, including WMs’ caste, education, political experience, and campaign priorities, as well as ward-level and GP-level demographic characteristics.¹⁵ Below, we provide an overview of the different sets of outcome measures.

4.2 Ward Member Level Outcomes

4.2.1 Knowledge

WMs’ Knowledge We collect data on knowledge from the baseline and endline WM surveys. At baseline, we ask WMs to list the steps required to implement different schemes. At

¹⁴Appendix G provides detailed descriptions of variable construction and reproduces the survey questions used to construct the principal knowledge, network, confidence, and conflict measures.

¹⁵Ward populations are obtained from the Bihar State Election Commission, while GP-level demographic characteristics are drawn from Census 2011.

endline, we construct four measures of knowledge. First, we measure formal knowledge of codified procedures required for scheme implementation. Second, we measure tacit knowledge related to informal implementation practices. Third, we construct a measure of procedural knowledge using scheme-specific factual questions related to implementation rules and processes. Finally, we measure knowledge of best practices for addressing common governance and implementation challenges. We aggregate these four measures into a Combined Knowledge Index. The construction of these indices is detailed in Section G.1. The first two draw on questions asking WMs to list the steps required to implement a range of schemes. Steps that are explicitly codified in official guidelines contribute to the Formal Knowledge Index, while steps that reflect commonly understood field practices contribute to the Tacit Knowledge Index; both are standardized relative to the control group. The Procedural Knowledge Index instead uses objectively scored questions about specific scheme rules — such as eligibility criteria and documentation requirements — where answers are coded correct or incorrect. Finally, the Best Practices Index uses scenario-based questions to capture whether WMs can identify effective, concrete solutions to common implementation challenges, distinguishing these from generic responses. The Combined Index aggregates all four.

Knowledge Flow To measure the informational content of peer interactions, we collect detailed records of discussions during peer meetings.¹⁶ For each discussion topic, we identify (if any) the WM who raised the issue and the WM who proposed a solution. We also record the content of the problem and the proposed solution.¹⁷

Using these records, we construct scheme-specific measures of exposure to peer learning. In particular, for each WM and scheme, we measure both the number of best practices to which the WM was exposed and the total time spent discussing that scheme. In the mediation analysis, we classify WMs as having above-median or below-median exposure to a given scheme.

¹⁶Each meeting included a trained note-taker responsible for recording the issues discussed, the participants contributing solutions, and the content of proposed solutions.

¹⁷A problem might be: *the GP Head is not releasing funds for the tap water scheme.* An example solution might be *Call for a ward sabha (community meeting), put forward the issue among the constituents, and make a joint representation to the GP Head asking him to release funds.* Alternatively, *Petition the Block Development Officer by writing a letter and copying higher-level officials.* In in-person meetings, we observed that WMs would occasionally discuss the precise wording of petitions to higher-level officials or exchange phone numbers of relevant bureaucrats when attempting to resolve implementation bottlenecks.

4.2.2 Networks

We measure networks using both baseline and endline surveys. At baseline, WMs report whether they know and discuss work-related matters with other WMs within and outside their GP. At endline, we first directly measure whether treated WMs know randomly selected members of their assigned peer groups (in the control arm, WMs are asked about members of fictitious groups), allowing us to verify whether the intervention led participants to form connections within their assigned peer groups. We then construct measures of three dimensions of professional and political networks: (i) connections with other WMs outside the GP, (ii) connections with block-level bureaucrats—specifically, the BDO and the BPRO, who are responsible for rural development and GP-related administration, and (iii) connections with political parties. We also construct a combined index aggregating these three dimensions. These measures allow us to assess whether the intervention expanded professional and political networks among WMs (for details see Section [G.2](#)).

4.3 Conflict

We use the endline WM survey to measure work-related conflict and WMs' relationships with key local actors. WMs report whether they have experienced conflicts related to their work with any public representative or government employee in the Panchayat, Block, or District. We construct separate indicators for conflict with the GP Head, GP NREGA Assisstnat (*Rozgar Sevak*), and GP Secretary (*Panchayat Sachiv*) .¹⁸

We also measure WMs' relationships with the GP Head and their participation in Gram Sabha meetings. The relationship measure is based on WMs' self-reported assessment of their relationship with the GP Head, while the Gram Sabha measure captures whether WMs attended at least four meetings. Further details on the construction of these measures can be found in for details see Section [G.4](#).

4.3.1 Agency

We measure agency along three dimensions: confidence in implementing schemes, willingness to adopt new technologies, and collective efficacy. First, using the baseline and endline WM surveys, we measure confidence by asking WMs to identify up to two schemes

¹⁸**GP NREGA Secretary (*Rozgar Sevak*)**: A village-level functionary responsible for assisting the Gram Panchayat in implementing NREGA, including maintaining programme records, facilitating work allocation, and supporting programme administration.

GP Secretary (*Panchayat Sachiv*): The administrative official of a Gram Panchayat responsible for maintaining official records and supporting the day-to-day administration of the Panchayat and the implementation of government programmes.

they feel confident implementing (for details see Section G.3). Second, we measure willingness to adopt new technologies through a sub-experiment in which a randomly selected subset of treated and control WMs was offered the opportunity to file complaints under Bihar’s grievance redressal scheme. Third, we measure collective efficacy using a petition exercise that assesses treated and control WMs’ ability to mobilise signatures demanding greater devolution of responsibilities to WMs.

4.4 Governance Outcomes

4.4.1 Gram Panchayat Development Plan (GPDP) Data

We obtain GPDP data from the eGramSwaraj portal.¹⁹ These plans detail proposed expenditures for the subsequent financial year for We use GPDP data for the 2024 – 25 financial year, which coincides with the period of our intervention. Using the project descriptions together with the corresponding theme and sector fields, we classify projects into scheme categories.²⁰ These data are not available at the ward level, so examine the impact of our intervention on planned spending priorities at the GP level. For further details see Section G.5.

4.4.2 National Rural Employment Guarantee Act Data

We scraped data on all NREGA job-cards in Bihar for our experimental districts in October 2024. Each job-card contains details on the applicant, whether they received work in the current year, and their prior work history. We use this data to construct two outcomes: NREGA work provision across treatment and control GPs during our experimental period; and potential self-dealing by WMs and GP heads.²¹

¹⁹eGramSwaraj is the Government of India’s online public portal for managing Gram Panchayat Development Plans (GPDPs), providing information on approved projects, their implementation status, and both planned and actual expenditures financed through Central Finance Commission grants.

²⁰The scheme categories are subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY), Health insurance (*Ayushman Card*), Education, Water conservation (*Jal Jeevan Hariyali*, JJH), Healthcare, Marriage assistance (*Mukhyamantri Kanya Vivah Yojana*, MKVY), Public grievance redressal (*Lok shikayat*), Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (*Nali-Gali*), Provision of tap water (*Nal-Jal*), Pension, Subsidised food rations (Public Distribution System, PDS), Public service delivery (Right to Public Services, RTPS), Educational financial assistance (Scholarship), Solar Street Lights, subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), and Entrepreneurship support (*Mukhyamantri Udyami Yojana*, MUY). Projects that could not be reliably classified into a specific scheme based on the available project description, theme, and sector fields were classified as “Uncategorized”.

²¹We define self-dealing as excess work provision to elected officials — above what would be expected if they participated in NREGA purely as ordinary workers — and use it as a proxy for corruption. Since some elected officials may legitimately be NREGA workers, we do not treat all work provision to elected officials as self-dealing; rather, it is the difference relative to control GPs that captures increases or decreases

4.4.3 Citizen Survey

We survey 9,699 citizens²² from treatment, spillover, and control areas. The survey captures citizens' preferences over public goods and government programs, assessments of public services in their ward, access to social welfare benefits, and perceptions of their WM.²³ Further details on the construction of these measures can be found in G.7 and G.8.

5 Empirical Analysis

Our experimental design gives rise to three broad classes of empirical specifications. We estimate (i) the direct effects of participation in peer groups on WM-level outcomes, (ii) spillover effects on untreated WMs within treated GPs, and (iii) the effects of the intervention on downstream governance outcomes measured at the GP $\times$ scheme level.

5.1 Direct Effects on WM-Level Outcomes

To estimate the direct effects of peer groups, we compare treated WMs, who were assigned to a peer group, with control WMs in control GPs. We estimate the following ANCOVA specification:

$$Y_i = \alpha + \beta \cdot TreatedWM_i + \gamma Y_{i,baseline} + \theta X_i + \Delta + \epsilon_i, \quad (1)$$

where Y_i denotes the endline outcome of interest for WM i , $TreatedWM_i$ is an indicator equal to one if the WM was assigned to a peer group, $Y_{i,baseline}$ is the baseline value of the outcome, where available, and Δ denotes district fixed effects. We always include the baseline value of the outcome when it is available, irrespective of whether it is selected by the covariate-selection procedure. The vector X_i contains additional baseline covariates selected using the double-selection LASSO procedure.²⁴ Standard errors are clustered at the GP level, the unit of treatment assignment. We estimate Equation 1 separately for each WM-level outcome, including knowledge, agency, and professional networks.

in corruption.

²²The sample includes around two citizens per ward from treatment and control areas and one citizen per ward from spillover areas.

²³The survey was conducted over the phone using contact information collected in 2021, resulting in relatively low response rates. Since the phone numbers were not tagged to wards, respondents could not always be matched precisely to specific wards within a GP.

²⁴The set of candidate controls includes ward-level characteristics such as distance to the nearest town, population, SC share, and reservation status, as well as WM-level characteristics including age, caste, gender, education, and other baseline characteristics.

5.2 Spillover Effects

To estimate spillover effects, we compare untreated WMs in treated GPs with untreated WMs in control GPs. We estimate the following ANCOVA specification:

$$Y_i = \alpha + \beta \cdot TreatedGP_i + \gamma Y_{i,baseline} + \theta X_i + \Delta + \epsilon_i, \quad (2)$$

where $TreatedGP_i$ is an indicator equal to one if the WM was untreated but belongs to a treated GP. All other variables are defined as above. Standard errors are clustered at the GP level.

5.3 Governance Outcomes

As noted above, we estimate the effect of the intervention on downstream governance outcomes at the GP $\times$ scheme level. We begin by estimating the average effect of treatment on planned expenditure using the following ANCOVA specification:

$$Y_{gs} = \alpha + \beta \cdot TreatedGP_g + \delta_s + \Delta + \theta X_g + \epsilon_{gs}, \quad (3)$$

where Y_{gs} denotes planned expenditure by GP g on scheme s , $TreatedGP_g$ is an indicator equal to one for treated GPs, δ_s denotes scheme fixed effects, Δ denotes district fixed effects and X_g is a vector of GP-level baseline characteristics (chosen via the double selection LASSO procedure). Standard errors are clustered at the GP level.

We then estimate extensions of Equation 3 that allow treatment effects to vary with the extent to which a scheme was prioritized by WMs and citizens. Specifically, we interact $TreatedGP_g$ with (i) $CampaignShare_{gs}$, the share of surveyed WMs in GP g who reported campaigning on scheme s , and (ii) $CitizenPreference_{gs}$, the share of surveyed citizens who reported that the local government should allocate additional spending to scheme s . These specifications allow us to test for both an overall increase in planned expenditure and a shift in the composition of spending towards schemes receiving greater support from WMs and citizens.

5.4 Randomization and Compliance

Take-up and Participation. In our baseline survey, an overwhelming majority of WMs (95%) expressed interest in connecting with other WMs and joining a peer group. Consistent with this, we see enthusiastic participation from WMs, with Over 95% of treated WMs participating in at least 1 peer group interaction (either in-person meeting or conference call), and 83% having participated in multiple interactions.

Summary Statistics and Balance. Using administrative data and our baseline survey, we present summary statistics and assess the validity of our randomisation. Since we randomised in two stages, first selecting GPs and then wards, we show balance at both the GP and ward levels. Tables 1, A6 and A7 present the results of balance tests. Table 1 shows that treated GPs and control GPs are balanced on a wide range of variables, including demographic and geographic characteristics, public good availability, and political reservation status.

Next, we establish balance at the ward level in Appendix Table A6. The average ward has 810 citizens, of which about 22% are SCs. The average WM is 38 years of age and has about 10 years of education. Since we oversampled SC WMs, a slightly higher share of our sample WMs (32%) are SCs. In other respects, our sample is representative of the 30,400 WMs in our 10 sample districts.

The next part of Appendix Table A6 focuses on WMs' prior experience and the issues they campaigned on. Several things are noteworthy. First, nearly 70% are first-time elected officials, and only 10% have family ties to current or former politicians, so it is not surprising that many are unfamiliar with government processes. Second, most WMs report campaigning on the local development schemes they manage: 82% of WMs discussed issues related to the drains and lanes scheme during their campaign, while 54% mentioned campaigning on the tap water scheme. Social protection programs were also mentioned: 18% of WMs campaigned on pensions, while 27% spoke about the housing subsidy scheme. The table also shows that treatment, control and spillover wards are balanced on these characteristics. Finally, Table A7 establishes balance over WMs' knowledge and pre-existing networks.

Peer Group Connections. Before turning to the impacts of the intervention, we verify that the peer groups successfully generated the intended connections among participants. At endline, treated ward members (WMs) are 51 percentage points more likely to report knowing a randomly selected member of their assigned peer group relative to control WMs, who were assigned to fictitious groups that never met. This large effect confirms that the intervention successfully created new connections across GPs. We return later to examine whether these new peer-group ties translated into broader professional and political networks.

6 Results

6.1 Knowledge

Direct effects. Our first main finding is that the intervention significantly improved learning among treated WMs. As described above, we measure WM knowledge at endline using four indices, which we combine into an overall index. Table 2 reports treatment effects across the five knowledge measures. Treatment increases the combined knowledge index by approximately 0.13 SD. These gains are driven primarily by improvements in tacit knowledge, alongside significant increases in *de jure* procedural knowledge and knowledge of governance best practices. Control group WMs also learn on the job: after 18 months in office, the share of scheme-implementation steps they correctly identified increased by 5.5 percentage (Appendix Figure A3). Yet treated WMs identify 10.3pp more steps than at baseline, indicating that peer groups nearly double politicians’ rate of on-the-job learning. Together, these patterns suggest that peer interactions facilitate the transmission of both informal know-how and concrete best practices, and that WMs are able to apply insights acquired during group discussions to practical situations.

Spillover Effects. We also find strong spillover effects of our intervention as shown in Table 3. The spillover effect on the combined knowledge index is approximately 0.08 SD, nearly two-thirds of the direct treatment effect. Given that each GP contains roughly ten spillover WMs and only two treated WMs, a back-of-the-envelope calculations suggests that spillovers account for 60-75% of the total knowledge gain due to the intervention.

Next, we present evidence that group identity and strategic considerations influence the diffusion of governance knowledge within the GP. Spillovers are stronger among WMs who share a social identity with the treated colleagues in their GP, and that these effects increase with the number of such treated peers (See Figure 3 and the corresponding Appendix Table A10). In particular, the effect on the combined knowledge index is more than twice as large when spillover and treated WMs share the same caste affiliation, and about 15% larger when they share the same religion. The pattern also extends to partisan identity: spillover WMs experience greater knowledge gains when more GP colleagues from the same party are treated, but no improvement when treated peers are associated with a different party.²⁵ These patterns suggest that identity-based ties facilitate the diffusion of governance knowledge within the GP.

²⁵As noted above, GP elections in Bihar are formally non-partisan. Political affiliation here refers to involvement with a political party outside the formal GP electoral process; in our data, this measure captures whether the WM or a member of their family is involved with a political party in any capacity.

We also explore whether strategic considerations influence spillover effects. In particular, WMs may have incentives to limit information sharing on schemes where resources are effectively constrained at the GP level, such that increased access in one ward reduces availability in others. Examples of such rivalrous include provision of tap water (*Nal Jal*), drains and lanes construction (*Nali Gali*), and NREGA (See Appendix section G.10 for details).

We examine whether spillovers are weaker for rivalrous schemes and find evidence consistent with this pattern (Figure 2).²⁶ Direct treatment effects are positive for both rivalrous and non-rivalrous schemes. While we cannot reject that direct treatment effects are the same for both categories, they are if anything larger for rivalrous schemes. The pattern differs markedly for spillovers. For non-rivalrous schemes, spillover effects are positive and statistically significant, whereas for rivalrous schemes they are statistically indistinguishable from zero. Moreover, we reject the null that the spillover effects are equal across the two types of schemes. This pattern is consistent with strategic withholding of information within GPs for rivalrous schemes, where increased access in one ward may come at the expense of others. By contrast, learning within peer groups—which comprise WMs across GPs and therefore not subject to local resource constraints—appears unaffected.

Heterogenous Treatment Effects on Knowledge. To explore treatment effect heterogeneity, we apply the causal forests method of [Wager and Athey \(2018\)](#) to estimate conditional average treatment effects (CATEs) for the knowledge index.

Panel A of Figure 4 presents the CATE distribution for direct effects on knowledge. The figure shows that most politicians are predicted to experience positive direct effects from the intervention: the median CATE is about 0.14 SD, and nearly the whole distribution lies to the right of zero. Panel B of Figure 4 presents the corresponding CATE distribution for spillovers. We see, similarly, that the median politician is predicted to experience about a 0.1 SD knowledge gain due to spillovers from treated WMs, and again the majority of the distribution lies to the right of zero. Reassuringly, these results are consistent with our baseline estimates, and indicate that most WMs are predicted to experience both direct and indirect benefits from the intervention.

Both histograms also demonstrate a significant degree of heterogeneity in treatment effects, i.e. some politicians are predicted to benefit much more from the networks intervention than others.

²⁶The corresponding tables can be found in the Appendix tables A8 and A9.

Who Benefits from Networks? We analyse correlates of the direct and spillover CATEs. Panel (a) of Figure A4 shows coefficients from a regression of the direct CATE on knowledge on each of the listed politician and group characteristics. We see that the strongest correlates of knowledge CATEs are baseline education, knowledge and confidence; in other words, advantaged WMs benefitted more from the intervention. In line with this, table A11 shows that the endline variance in knowledge in treated groups is higher than the variance in knowledge in the fictitious control groups. Group characteristics also predict knowledge effects: group mean education is an important predictor; group baseline knowledge and network strength are positively correlated with treatment effects, but their predictive power is relatively weak and matter less than individual characteristics.²⁷

Panel (b) of Figure A4 presents correlates of spillover effects. Here we see more limited evidence that more advantaged WMs experience stronger spillover effects: the correlation with education is positive, but weaker than for direct effects, while we also see weak positive correlations for baseline knowledge and network quality.

6.2 Agency

Next, we examine how the intervention affected politicians' agency and find that participation in peer networks enhanced WMs' sense of agency across multiple domains. Recall that we measure agency in three ways: (i) WMs' self-reported confidence in performing governance tasks²⁸, (ii) their ability to mobilise signatures for a petition, and (iii) their willingness to use the grievance redressal system to address service delivery issues in their constituency.

Confidence. Peer networks significantly improved WMs' confidence in their own capacity to govern. In our endline survey, treated WMs report greater confidence in their ability to implement key government programs. Specifically, they score 0.09 SD higher than control WMs on a standardized index capturing confidence in implementing multiple schemes (Column 1, Table 4). These results suggest that peer engagement facilitates meaningful learning that translates into greater self-efficacy.

Collective Action. Our second measure of agency is the willingness and ability to mobilise people. To capture this, we implement a sub-experiment on collective action. Approximately 790 randomly selected WMs, from both our control and treatment groups,

²⁷We pre-specified four key group-level attributes that would predict learning: group education, experience, knowledge and networks.

²⁸See Section G.3.

were invited to lead a petition on a governance issue. Specifically, WMs were invited to lead a petition on one of two issues: restoring WMs' role in managing provision of tap water (*Nal-Jal*) projects in their wards; or granting WMs greater autonomy in NREGA implementation. We then measure the number of signatures each WM mobilised.

We find that treated WMs—those assigned to peer groups—are 7.7 percentage points more likely to mobilise at least one signature, a 40% increase relative to the control-group mean, and 6.1 percentage points more likely to mobilise a signature from another WM (Columns 2 and 3, Table 4). Consistent with these extensive-margin effects, Appendix Table A12 shows that the total number of signatures collected also doubles. We find no evidence that treated and control WMs differ in their beliefs about the importance of the underlying policy issue, suggesting that the results are not driven by differences in issue salience. Instead, they are consistent with participation in the peer groups increasing WMs' ability to mobilise others and coordinate collective action.

Taken together, these results suggest that peer networks can be powerful tools for enhancing political agency. By boosting confidence and enabling collective action, peer groups can equip local leaders—especially first-time politicians—with the tools they need to govern more effectively.

Grievance redressal. Finally, we examine whether the intervention affected WMs' use of formal grievance mechanisms. We informed a randomly selected subset of WMs about Bihar's Grievance Redressal Scheme and tested whether treated WMs were more likely to act on this information. The scheme allows citizens to file complaints about service delivery issues and requires the state government to convene a hearing within 60 days. [Sharan and Kumar \(2025\)](#) shows that elected representatives use this mechanism to trigger government action, with such complaints leading to improvements in public services.

We measure whether treated WMs are more likely to file a complaint. Despite the gains in knowledge, confidence, and collective action documented above, we find no evidence that peer groups increase WMs' likelihood of filing a complaint under the scheme (Table 4, Column 4). We have two explanations for this null result: first, take-up of the grievance redressal scheme was very low, with only about 6% of WMs filing complaints. [Sharan and Kumar \(2025\)](#) also show that filing rates are very low without outside assistance with completing the application. Another explanation is that improved knowledge enable WMs to handle governance issues in other way without resorting to filing grievances via the redressal scheme.

6.3 Professional Networks and Relationships with Government Actors

Professional Ties. Beyond learning and agency, the intervention also shaped the professional and political networks of treated WMs. Recall that we measure three dimensions of networks: connections with other WMs outside the GP, interactions with higher-level bureaucrats, and connections with political parties. Treated WMs exhibit stronger networks across all three dimensions (Table 5). The combined network index increases by 0.15 standard deviations, with the largest gains in cross-GP WM connections (0.15 SD), followed by bureaucratic networks (nearly 0.07 SD) and political networks (nearly 0.05 SD). The intervention directly expands WMs' connections with other WMs. However, the increase in ties to block-level bureaucrats and parties is not automatic, and suggests that peer groups shared contacts—our moderators directly observed some instances of this—and inducted peers into their parties. In our context, only about 20% of WMs are associated with a party, and these WMs are generally more knowledgeable and connected than the average WM. There is likely to be positive selection of WMs into parties, but parties could also support WMs with knowledge and resources that enable them to govern better.

Conflict. While the peer group intervention expanded WMs' professional networks beyond the GP, increasing their exposure to ward members from other GPs, block-level officials, and political actors, it also affected relationships with bureaucrats and politicians within the GP. Prior work documents persistent tensions between ward members and GP Heads (Sharan, 2021), who are formally in charge of the council and retain primary charge responsibility for project execution. a pattern also reflected in our field notes from peer meetings.

We find that participating in peer groups intensifies these within-GP frictions. Treated WMs are more likely to report conflicts with the GP Head, as well as with village-level officials, including the NREGA *Rozgar Sevak* and the GP Secretary. These staff are responsible for day-to-day village administration and also play a role in facilitating access to some social protection schemes. Treated WMs are also less likely to attend Gram Sabha meetings (Table 6). We see no such pattern for spillover WMs.

These results suggest that increases in knowledge, confidence and agency have the potential to disrupt existing hierarchies and working relationships within the GP. The co-existence of professional gains and heightened conflict raises an important question: how do these opposing forces shape governance outcomes? On the one hand, improvements in learning and agency may enable more effective planning and implementation. On the other hand, increased conflict may hinder coordination during these collective decisions.

6.4 Overall Impacts on Governance

To examine the downstream effects of the intervention on governance outcomes, we turn to the Gram Panchayat Development Plan (GPDP), the annual planning process through which local infrastructure projects are proposed and public resources allocated. The GPDP records planned spending across government schemes for the 2024–25 financial year. As planning decisions are recorded at the GP level and very few projects are assigned to individual wards, we conduct our analysis at the GP level, comparing treated GPs—which experienced both direct knowledge gains and spillover benefits—against control GPs.

Our main outcome of interest is total planned expenditure. We ask two related questions. First, do treated GPs allocate more resources overall (an *allocation effect*)? Many GPs are so capacity constrained that their development plans do not utilise the available resources. If treated WMs have greater capacity and agency, this might increase the scale of development plans. However, more ambitious planning need not be welfare-improving, especially if they fail to reflect citizens’ preferences. We therefore also ask whether treated GPs allocate more resources towards the public goods and schemes that citizens value or WMs campaigned on (an *alignment effect*).

Allocation Effects. Treated GPs allocate approximately 3% more spending per scheme than control GPs, corresponding to an increase of INR 16,674 per scheme (Column 1, Table 7). These gains do not come at the expense of neighbouring control GPs: blocks with a higher share of treated GPs if anything also plan higher expenditures, though this effect is not statistically significant.²⁹

Alignment Effects. We measure alignment effects in two ways. First, we examine whether treated GPs allocate more resources towards the schemes WMs campaigned on during elections. To do so, we compute the share of WMs in a GP who reported campaigning on each scheme at baseline and interact this share with treatment status (Table 7, column 2).³⁰

Even in control GPs, schemes supported by a larger share of campaigning WMs have higher planned expenditure. The interaction between treatment status and campaign support is positive and statistically significant, while the coefficient on *Treated GP* alone is close

²⁹We estimate a regression of GPDP expenditures at the block level on the share of treated GPs in the block. The point estimate is INR 267,000 with a standard error of 376,000.

³⁰The corresponding estimates for the number of planned projects are similar: treated GPs plan more projects, and project allocations are more strongly aligned with both WMs’ campaign priorities and citizens’ preferences (Appendix Table A17).

to zero. This implies that when no WM in a GP campaigned on a scheme, treated and control GPs allocate similar levels of spending. By contrast, treatment increases spending on schemes that featured more prominently in WMs' electoral campaigns. The magnitude of the interaction effect implies that moving from a scheme on which no WM campaigned to one on which all WMs campaigned increases planned expenditure by approximately 30% relative to the control-group mean.³¹ Even though WMs tend to campaign on local priorities, we next examine the interaction with citizens' preferences more directly.

Specifically, we test whether treated GPs allocate more resources towards the schemes valued by their citizens. For each scheme, we calculate the share of surveyed citizens who report that the local government should spend more on it and interact this measure with treatment status.³² The results are reported in column 3 of Table 7. The coefficient on *Treated GP* alone is close to zero, implying that for schemes that few citizens prioritise, treated and control GPs allocate similar levels of spending. The interaction between treatment status and citizen preferences is positive and statistically significant, indicating that treatment increases spending on schemes that are highly valued by citizens. The magnitude of the interaction effect implies that moving from a scheme that no citizen value to one that all citizens prioritise increases planned expenditure by 44% relative to the control-group mean.³³

A potential concern is that the alignment effects documented above could be an artefact of the allocation effect: if treated GPs simply allocate more resources across the board, they are mechanically also more likely to spend on schemes that citizens prefer or WMs campaign on. Our results are inconsistent with this: the coefficient on *Treated GP* in columns 2 and 3 is close to zero, indicating that treated GPs do not spend more on public goods that few WMs campaigned on or that few citizens value. Treatment does not increase spending across the board. Rather, there is a shift in expenditures towards schemes that enjoy greater support from citizens and were deemed local priorities by elected leaders.

Figure 5 provides an alternative way of visualizing the alignment effects. For each GP,

³¹The GPDP data cover 18 schemes, whereas WMs report campaigning on only eight schemes in the baseline survey. Our main specification therefore includes all 18 schemes and codes the campaign-share variable as zero for schemes that were not the subject of electoral campaigns. In the appendix Table A13, we restrict the analysis to the eight schemes on which WMs report campaigning. The estimated effects are larger in magnitude in this restricted sample.

³²Since citizen preferences are measured at endline, a potential concern is that treatment itself affected stated preferences. Appendix Table A15 shows no systematic differences in citizens' scheme preferences between treated and control GPs.

³³Alignment may partly reflect treated WMs being better informed about what citizens want. In the endline surveys, in addition to eliciting citizen preferences, we also asked WMs which schemes they believed citizens wanted the local government to prioritize. The correspondence between WM beliefs and reported citizen preferences is stronger in treated GPs (Appendix Table A16), suggesting that improved knowledge of citizens' priorities may account for part of the spending-alignment effect

we distinguish between schemes on which no WM campaigned and the scheme receiving the greatest campaign support, based on the share of WMs who reported campaigning on each scheme. We estimate separate specifications for these two categories and plot the implied treatment effects, calculated as the sum of the coefficient on *Treated GP* and the corresponding interaction term. Panel A reports these estimates. Panel B implements the same exercise using citizen preferences, showing treatment effects on highly popular public goods and those valued by no citizens within each GP. All specifications control for district and scheme fixed effects. The underlying regression results are reported in Appendix Table [A18](#).

The figure highlights the substantial heterogeneity underlying the average treatment effect. For schemes on which no WM campaigned, the estimated treatment effect is approximately INR 23,000, about 6% of the control mean. By contrast, treated GPs allocate approximately INR 130,000 more to the scheme receiving the greatest campaign support, a 35% increase relative to the control mean. The pattern is even sharper for citizen preferences: the treatment effect is close to zero—approximately INR 4,000—for schemes that very few citizens prioritise, compared with approximately INR 127,000 (a 34% increase) for the scheme receiving the greatest citizen demand. These patterns show that the additional planned spending in treated GPs is concentrated in schemes receiving the strongest support from WMs and citizens, rather than reflecting an increase in spending across all schemes.

Incentive Effects. We also provide evidence that improvements to development plans are shaped by political incentives. Increases in GPDP expenditures are concentrated in electorally competitive GPs, where the Head won narrowly in the previous election (Table [A14](#)). This result suggests that electoral incentives influence the GP's likelihood of translating WMs' improved capacity into better governance.

In this sense, our results consistently indicate that more advantaged GPs benefit more from our intervention: direct effects on learning are larger for more educated and knowledgeable WMs; spillover effects are stronger in more homogeneous GPs that are less polarised along caste, religious or partisan lines; and development plan effects are strongest in electorally competitive GPs.

Together, these results suggest that treated GPs are more effective in translating citizens' priorities into concerted government action. They not only plan more ambitiously, but also allocate resources in ways that are more closely aligned with their constituents' priorities.

6.5 Citizen Perceptions of Governance

Our previous results show that development plans in treated GPs spend more on public goods and schemes prioritised by WMs and citizens. We next ask whether these planning gains are reflected in citizens' perception of governance quality and evaluations of their elected representatives. This is a demanding test, since GPDP projects may take time to move from planning to implementation, and citizens may not attribute completed projects to their WM as they stem from collective decisions.

Citizen-reported outcomes. We consider two sets of outcomes: citizen ratings of public goods and services, and reported access to welfare schemes (Appendix Table A19). We find no statistically significant effects on either dimension.³⁴ As noted earlier, however, the citizen survey suffered from low response rates because phone numbers dated from 2021, which limits our ability to detect downstream effects at the ward level.

Interpreting the null effects. One potential explanation for the absence of detectable impacts in the citizen survey is timing. While the intervention led to improvements in planning and alignment, these gains may not yet have translated into observable welfare improvements by the time citizens were surveyed.

As described above, the citizen survey was conducted between October 2024 and February 2025 (see Timeline in Figure 1). However, GPDP plans pertain to the 2024 – 25 financial year, and many planned projects are only implemented towards the end of the fiscal year and completed even after that. Thus, improvements in planning need not coincide temporally with downstream outcomes captured in the citizen survey.

To assess this possibility, we conducted an independent field audit to verify whether planned projects were implemented and when construction occurred. In July-August 2025, we deployed survey teams to audit 149 randomly selected planned projects across 54 GPs in two districts. Survey teams were able to locate 51% of the sampled projects on the ground (Appendix Table A20), indicating that GPDP projects do not just exist on paper but are in the process of being implementing. Among projects that were found, more than half were constructed after the citizen endline survey was completed (see Figure A5).

These findings indicate that a substantial share of implementation occurred after the period in which citizen outcomes were measured. Moreover, as Appendix Table A21 shows, even when projects are built, citizens do not always attribute them to WMs. This is not surprising since GP governance is the collective responsibility of the elected council

³⁴We similarly find no detectable effects on citizens' assessments of WMs' performance, public image, electoral prospects, or coordination with other officials (Appendix Table A22)

and GP head, and projects are seldom attributable solely to a single WM.³⁵ The substantial within-GP spillovers in governance knowledge that we document may also contribute to weakening citizens' evaluation of their WM relative to the other WMs in their GP. Delayed implementation, attribution frictions and sizeable within-GP spillovers help explain how citizens can perceive limited improvements in immediate service delivery and their WM's performance in spite of their stronger capacity and improved development plans.

6.6 Corruption and Rent-Seeking

Another concern is that politicians may learn negative behaviours from their peers ([Sacerdote, 2011](#)). In particular, politicians may learn more effective strategies to extract rents—a particularly salient concern in Bihar ([Banerjee et al., 2020](#)). We test for this using two complementary proxies for corruption: self-dealing of NREGS benefits ([Jeong et al., 2023](#)), which we measure using rich administrative data on beneficiary work histories and payments; and citizens' reports of bribe requests from WMs, which we capture in our endline survey.

NREGA self-dealing. Following [Jeong et al. \(2023\)](#), we identify WMs among the universe of NREGS beneficiaries using names and family identifiers. Approximately 15.7% of WMs in our sample of GPs have received NREGS benefits themselves. Our primary outcome is the share of total NREGA person-days in a GP-year accounted for by matched WMs. We find no difference between treated and control GPs, whether we consider the full 2023 – 25 period or only 2024 – 25, by which point four of the six peer interactions had occurred (Table [A24](#), Panel A, columns 1 – 2). Treatment also has no effect along either the extensive margin – treated WMs are no more likely to appear in the administrative data – or the intensive margin – conditional on appearing, they do not accumulate more person-days than control WMs (columns 3 – 6).³⁶

Bribe-taking. In our endline survey, we ask citizens whether they accessed any of five major welfare programmes during the intervention period: NREGA, rations, pensions, toilets, and housing. We then test whether citizens in treated wards are more likely to

³⁵Citizens attribute WMs some responsibility for project implementation in 36.1% of cases (Appendix Table [A21](#)). However, when asked to identify the main actor responsible for implementation, they rarely identify the WM (see Appendix Table [A23](#)).

³⁶Treatment also has no detectable effect on broader NREGA employment outcomes, including total person-days, the number of households receiving work, and person-days worked by SC and female workers (Appendix Table [A25](#)). One possible explanation is that WMs have limited authority over NREGA work-allocation and implementation decisions.

report paying bribes to WMs. Reported bribe-paying is rare, occurring in fewer than 5% of instances. We find no consistent evidence of increased bribe-taking: the combined index across all schemes shows a small, statistically insignificant treatment effect (Table A24, Panel B, column 6).

There are of course limitations to both these corruption measures. The NREGS self-dealing measure only captures misappropriation of workfare benefits and does not capture leakages in materials expenditure. Similarly, there are well-known limitations to self-reported bribe data. Nevertheless, these limitations notwithstanding, our evidence from both administrative data and citizen surveys suggests that the intervention did not meaningfully affect corruption or rent-seeking behaviour.

6.7 Robustness

Finally, we assess the robustness of our estimates.

Robustness. All regressions employ controls selected via a double-selection LASSO procedure. In the appendix, we show that our results are robust to omitting all controls (Appendix Table A26), re-clustering standard errors at the peer-group level (Appendix Table A27), a robustness test that Cai and Szeidl (2018) also implement, and employing alternative measures of WM learning. In our main specification, a WM is coded as exposed to a best practice if it was discussed during a meeting they attended. We show that this result is almost identical when including a leave-one-out measure that excludes solutions proposed by the WM themselves (Appendix Table A28). This is not surprising since each WM’s contribution is a small share of the total knowledge shared by the group of 10-12 WMs.

Attrition. We successfully re-surveyed 85% of the baseline sample at endline, and describe how we handle attrition in more detail in Section F. Retained WMs differ modestly from attrited WMs on some baseline characteristics, including caste, education, baseline knowledge, and network measures (Appendix Tables A29 and A30). However, there is no differential attrition across treatment groups. Moreover, among the WMs we do reach, treatment, control, and spillover WMs are balanced on a broad set of baseline characteristics (Appendix Tables A31 and A32).

Our direct and spillover estimates are robust to doubly robust estimators that adjust for attrition based on baseline covariates (Appendix Tables A33 and A34). Lee bounds, which make no parametric assumptions about the attrition process, also support the main

findings. In the treatment-versus-control comparison, all lower bounds on treatment effects are positive, and the lower bounds for knowledge, networks, and the relationship with the GP head are positive and statistically significant (Table A35). Together, these checks suggest that attrition is unlikely to explain our main findings.

7 Information Exchange and Peer-Group Quality

The previous section described the average effects of peer groups on learning, agency, professional relationships and governance outcomes. We next examine the mediating role of information exchange within peer groups. We do so in two steps. First, we ask whether treatment effects are larger in groups that exchanged more information during meetings. Second, we examine whether the effectiveness of peer-group interactions can be predicted ex ante using baseline characteristics.

7.1 Information Exchange and Treatment Effects

We first examine whether groups that exchange more information during meetings exhibit larger gains in learning, agency, and professional networks. Our measure of meeting quality is the number of best practices shared during group discussions. This gives us a proxy for the richness of information that each group exchanged about every major scheme. We then estimate heterogeneity by whether a group lies above or below the median of the scheme-specific distribution.³⁷ This allows us to test whether WMs in groups that exchanged more information about a particular scheme learn more about that scheme.

The results are summarized in Figure 6.³⁸ While the measures of discussion quality and information exchange emerge after initial treatment assignment, they nonetheless allow us to examine how treatment effects are associated with the level of information exchange.

Learning. We begin by examining whether learning gains are concentrated among groups that exchange more information. We find strong evidence that this is the case (Panel A of Figure 6). In particular, the combined knowledge index increases by approximately 0.08 SD for WMs in groups that exchanged an above-median number of best practices, while estimated effects for WMs in below-median groups are close to zero.

We find similar patterns when examining communication through *WhatsApp*. In Appendix Section E, we show that groups that exchange more messages exhibit greater learn-

³⁷Appendix Table A36 summarizes the distribution of best-practice exchange across schemes.

³⁸The corresponding tables can be found in the Appendix Tables A37, A38 and A39.

ing. Consistent with the meeting-based results, groups that exchange more scheme-specific messages also exhibit greater learning on those schemes (Tables [A40](#) and [A41](#)).³⁹

Agency. Confidence gains are also stronger among groups that exchange more information. WMs in groups with below-median levels of best-practice exchange do not experience significant improvements in confidence, while treatment effects rise to approximately 0.18 SD among WMs in groups with above-median levels of information sharing (Panel A of Figure 6).

We find weaker evidence of heterogeneity for collective action. While the coefficients for WMs in above-median groups are positive and larger than those for WMs in below-median groups, we cannot reject the null hypothesis of equal effects across the two sets of groups (Panel B of Figure 6). The pattern for grievance filing is different. As shown above, we found no average treatment effect on grievance filing. However, the heterogeneity analysis suggests that the estimated effect is positive for WMs in groups that exchanged more information, while the estimate for WMs in below-median groups is close to zero (Panel B of Figure 6).

Professional Networks. We observe a similar concentration of effects for professional networks. The treatment effect on the combined network index is approximately 0.17 SD for WMs in above-median discussion groups. In contrast, the point estimate for those in below-median groups are less than half in size and statistically indistinguishable from zero (Panel A of Figure 6). This pattern mirrors the heterogeneity observed for learning and confidence, suggesting that richer peer interactions facilitated not only the exchange of information but also the formation of durable professional ties.

Collectively, these results suggest that groups which exchanged more information during group meetings and calls experience larger learning, agency and network gains. The strongest patterns emerge for learning, confidence, and professional networks, while we also find suggestive evidence that richer peer interactions facilitate the adoption of formal grievance mechanisms. While these patterns should not be interpreted causally—since we could not randomly assign the level of information exchange and could thus capture other group characteristics—they are consistent with information sharing playing an important mediating role in driving the effects we observe.

³⁹The interaction of treatment with the binary measure of above-median message exchange has a p-value of 0.168 (Table [A40](#)). However, when we use a continuous measure of the number of scheme-related messages exchanged, the effect is statistically significant at the 10% level (Table [A41](#)).

7.2 Can We Predict Meeting Quality?

Having shown that groups exchanging more best practices exhibit stronger learning gains, we examine whether such variation in meeting quality can be predicted *ex ante*. This exercise sheds light on two related questions: First, how predictable is learning across groups? Second, can group composition predict information exchange?

To this end, we use 142 baseline predictors measured at the individual, group, ward, and GP levels to predict the level of information exchanged by groups. To maintain consistency with our main analysis, we partial out scheme and district fixed effects from both the predictors and the outcome, and predict the residualized number of solutions shared by each group.

We consider two predictive models. First, we estimate a random forest using 2,000 trees (minimum node size of 15), tuning `mtry` over a grid.⁴⁰ The model has limited predictive power, achieving an R^2 of just 0.006, indicating that baseline characteristics explain very little of the variation in meeting quality. Nevertheless, groups predicted to exchange more best practices exhibit significantly greater learning, with the combined knowledge index increasing by 0.059 SD ($p < 0.05$) (Panel A, Table 8).

Second, we estimate a cross-validated LASSO using the same set of residualized predictors. Predictive power remains similarly limited, with an R^2 of 0.004. However, groups with above-median predicted meeting quality display learning gains that are 0.042 SD larger, although the estimate is less precise ($p = 0.12$) (Panel B, Table 8).

Taken together, these results suggest that the effectiveness and quality of peer-group interactions are difficult to predict using baseline characteristics on group composition alone. It is not the case, for instance, that having more educated or knowledgeable group members strongly predicts the level of information exchange or learning gains. At the same time, the limited variation that can be predicted is positively associated with subsequent learning gains. These findings suggest that the factors driving successful peer-group interactions may be difficult to observe prior to implementation.

8 Cost-Benefit Analysis

We assess the cost-effectiveness of the intervention by comparing total programme costs to the resulting increase in public spending at the GP level. Total intervention costs — including facilitators and logistics for meetings — amount to INR 12.07 million (approximately USD 133,700 at an exchange rate of INR 90.27 per USD). Using our estimated treat-

⁴⁰Predictions are out-of-bag (OOB): each observation is predicted only by trees for which it was excluded from the bootstrap sample.

ment effect on GP-level spending, the intervention is projected to generate a total planned increase in public expenditure of INR 308.25 million (USD 3.41 million) across the 968 treated GPs. To provide a conservative lower bound, we further adjust this figure to account for the fact that only 51 percent of approved projects were implemented (though the eventual implementation rate is likely to be higher). Under this adjustment, the realised increase in public spending equals INR 157.21 million (USD 1.74 million). Even under this conservative assumption, the intervention yields approximately USD 13.0 in additional public spending for every dollar spent on programme implementation.

9 Conclusion

This paper shows that peer networks can meaningfully improve the governing capacity of local politicians. In a large-scale field experiment among ward members in Bihar, India, we find that structured cross-village peer interactions substantially expand politicians' professional networks and facilitate learning. Peer groups increase treated politicians' knowledge of governance processes and best practices, and roughly double the rate of on-job learning. These learning gains spill over to untreated colleagues who serve on the same village council, and account for a sizeable share of the knowledge gain due to the intervention. Spillovers are particularly strong when colleagues share a group identity and there are few strategic incentives to withhold information. Increased knowledge translates into higher confidence and agency, and ultimately into better governance: treated councils allocate more spending to citizens' priorities and politicians' campaign commitments.

The results have clear policy implications for low-capacity settings. Rather than relying on formal training or top-down oversight, governments can strengthen local governance by facilitating horizontal learning among elected leaders. Such peer-based interventions are not only scalable but also highly cost-effective: back-of-the-envelope estimates suggest that each dollar spent generates roughly USD 25.5 in planned public spending and USD 13 in realised public-good creation. Large spillovers also make peer networks an attractive complement to decentralisation and political inclusion reforms.

Several questions remain for future research. First, more work is needed to understand the micro-mechanisms of learning within peer groups, including how deliberation, leadership, and imitation shape knowledge transmission. Second, our findings suggest that learning and spillovers are mediated by social identity, with caste and religion influencing who learns from whom. Future studies could examine how group composition and institutional design affect these dynamics, and whether peer learning generates durable changes in political behaviour and governance over longer horizons.

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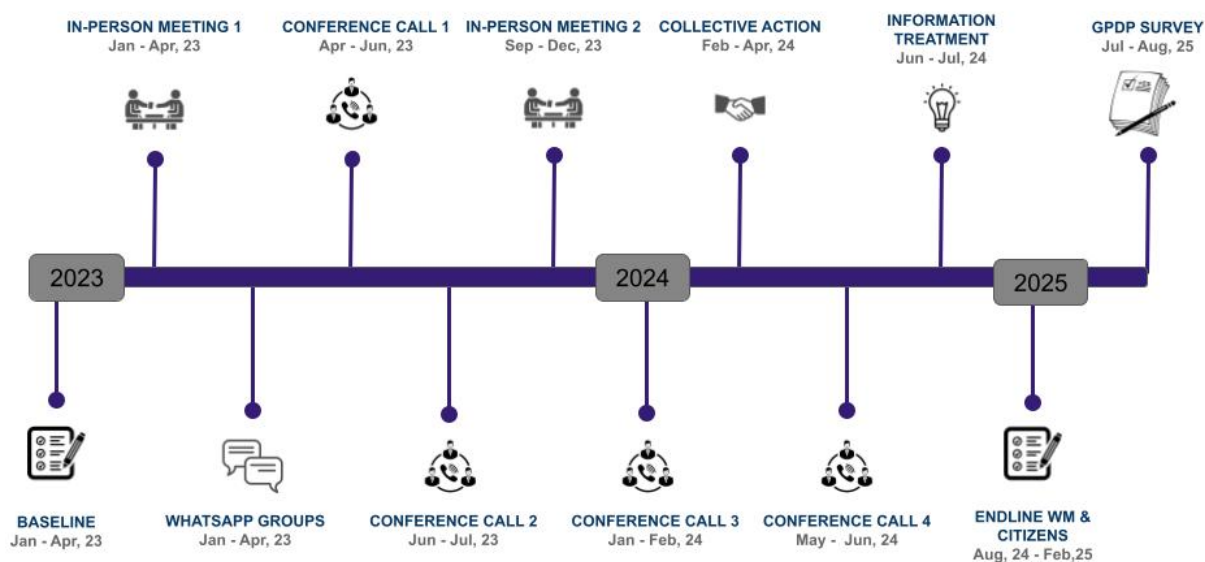
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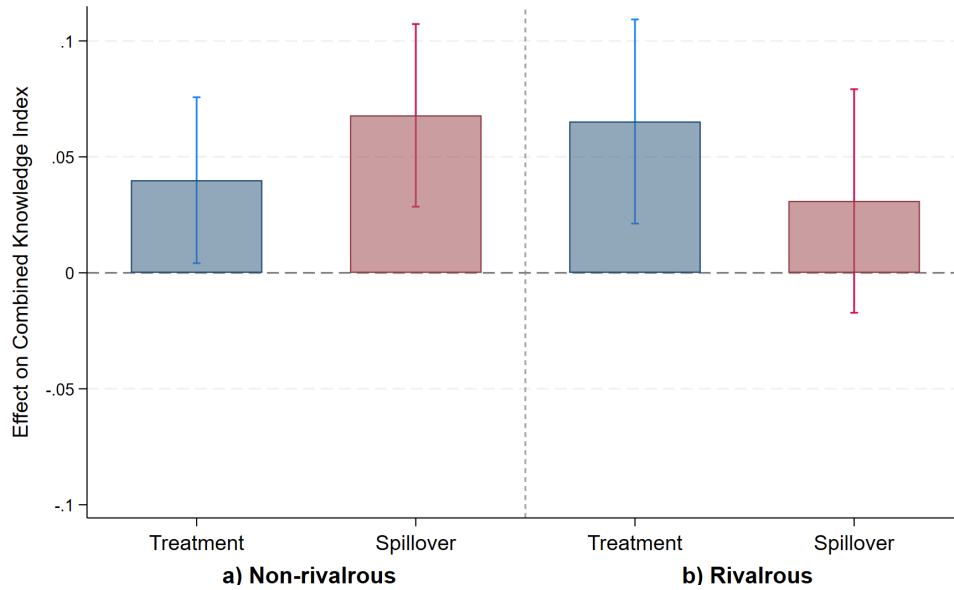
A Main Figures

Figure 1. Intervention Timeline



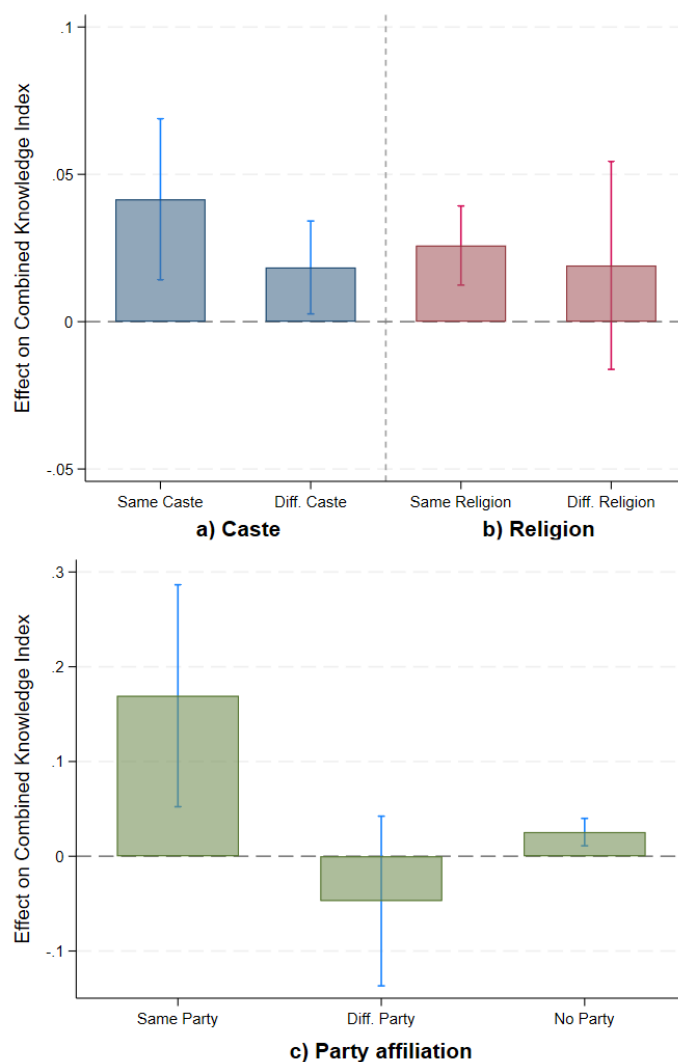
Notes: The above figure details the timeline for the peer groups intervention. This includes the baseline survey, the endline survey, the GPDP audit survey, the main experiment of peer group discussions (split into a series of 6 meetings, two in-person, four online), the creation of WhatsApp groups, along with the sub-experiments on collective action and grievance redressal.

Figure 2. Direct and Spillover Effects for Rivalrous vs Non-Rivalrous Schemes



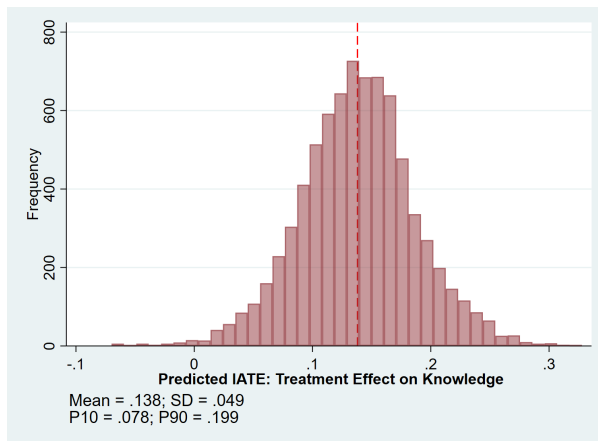
Notes: The above figure shows the direct and spillover effects on the combined knowledge index at endline for rivalrous and non-rivalrous schemes. Combined knowledge index is determined by taking the mean of formal, tacit, procedural and best practices index (taken from the endline survey) and standardizing them using the control mean. Details on the composition of formal, tacit, procedural and best practices index are given in Appendix G.1. We estimate effects of knowledge on ward members for each scheme. Rivalrous schemes refer to any scheme whose increase in demand made by a ward member for their own ward would affect the demand for the same scheme in another ward. This includes schemes such as Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (Nali Gali) and Provision of tap water (Nal Jal). Subsidy on House construction (Pradhan Mantri Awas Yojana, PMAY), Health insurance (Ayushman Card), Solid and liquid waste management (Lo-hiya Swachh Bharat Abhiyan, LSBA), Subsidised food rations (Public Distribution System, PDS), Solar Street Lights and Subsidy on Toilet construction (Swachh Bharat Abhiyan, SBM) on the other hand have been categorised as non-rivalrous. Further details on this classification is given in Appendix G.10. The treatment effect for non-rivalrous schemes are estimated in a regression that interacts the treatment ward with a dummy that identifies a scheme as rivalrous, while including the treatment and rivalrous dummy as separate covariates. The coefficient for the treatment ward in the regression is taken as the effect of treatment on knowledge for non-rivalrous schemes. Spillover effects are also estimated using a similar regression where we interact spillover ward dummy with a dummy that flags rivalrous schemes. Part a) shows the direct and spillover effects for non-rivalrous schemes whereas Part b) show the treatment and spillover effects for rivalrous schemes. Controls for treatment and spillover regressions include baseline knowledge, confidence, education, age, dummies that control for access to local bureaucrats and connectivity through phone, networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, if ward member received training and additional dummies that control for access to other local bureaucrats. Controls for both treatment and spillover regressions were determined using double select lasso. The knowledge index is standardised using the control mean. Error bars show 90% confidence intervals. Standard errors are clustered at the UGP level. All regressions control for district and scheme fixed effects.

Figure 3. Heterogeneity in Spillover Effects: Number of Treated Ward Members in own/different community/party within GP

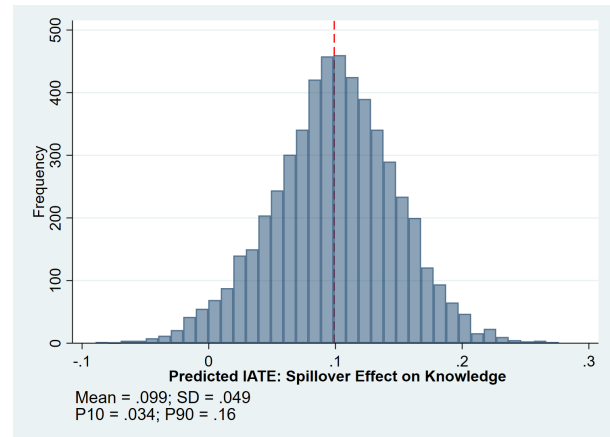


Notes: The figure shows the spillover effect on combined knowledge index for ward members that have a higher number of treated ward members of their own caste, religion or political party in their GP. Combined knowledge index is determined by taking the mean of formal, tacit, procedural and best practices index (taken from the endline survey) and standardizing them using the control mean. Details on the composition of formal, tacit, procedural and best practices index are given in [G.1](#). Caste, religion and party affiliation of each ward member is reported in our baseline survey. We run separate (caste, religion and party affiliation) regressions to see the effect on knowledge when treated ward members have more ward members of the same caste, religion or political party in their GP respectively. For part a), we regress the combined knowledge index on the count of treated WMs of the same caste in the WM's GP and on the count of treated WMs in GP belonging to a different caste. The first bar plot in part a) shows the coefficient for count of same caste treated WM, and the one to its right shows the coefficient value for count of different caste WMs. Similarly, in part b), we regress on count of treated WMs in GP belonging to the same religious faith and on count of treated WMs belonging to other religious faiths in the GP separately. The first bar in part b) plots the coefficient for the count of WMs in GP belonging to the same religious faith while the bar beside it plots the coefficient for count of WMs from other religious faiths. In part c) we regress on count of treated WMs in GP belonging to same, different and no political parties. The first, second and third bar in part c) plot the coefficients for count of WMs in GP who are in same, different and no party respectively. Controls for each regression includes baseline combined knowledge index, confidence, education, age, caste, dummies that control for access to local bureaucrats and connectivity through phone, networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, if ward member received training and additional dummies that control for access other local bureaucrats. Controls for the spillover regressions are determined using double select lasso. The knowledge index is standardised using the control mean. Error bars show 90% confidence intervals.

Figure 4. Distribution of Heterogeneous Treatment and Spillover Effects for Combined Knowledge Index



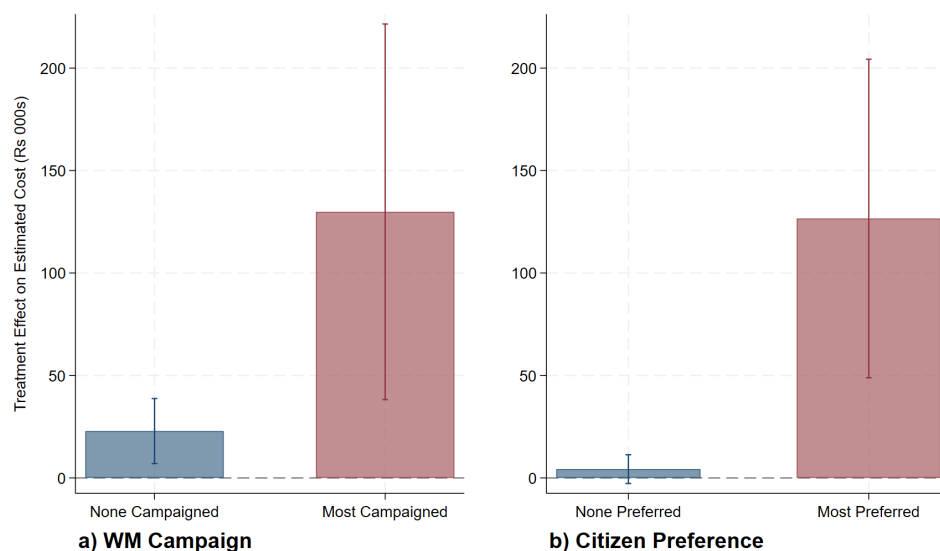
(a) Distribution of Predicted IATE (controlling for Individual and Group Characteristics)



(b) Distribution of Predicted Conditional Spillover Effects (controlling for Individual and Group Characteristics)

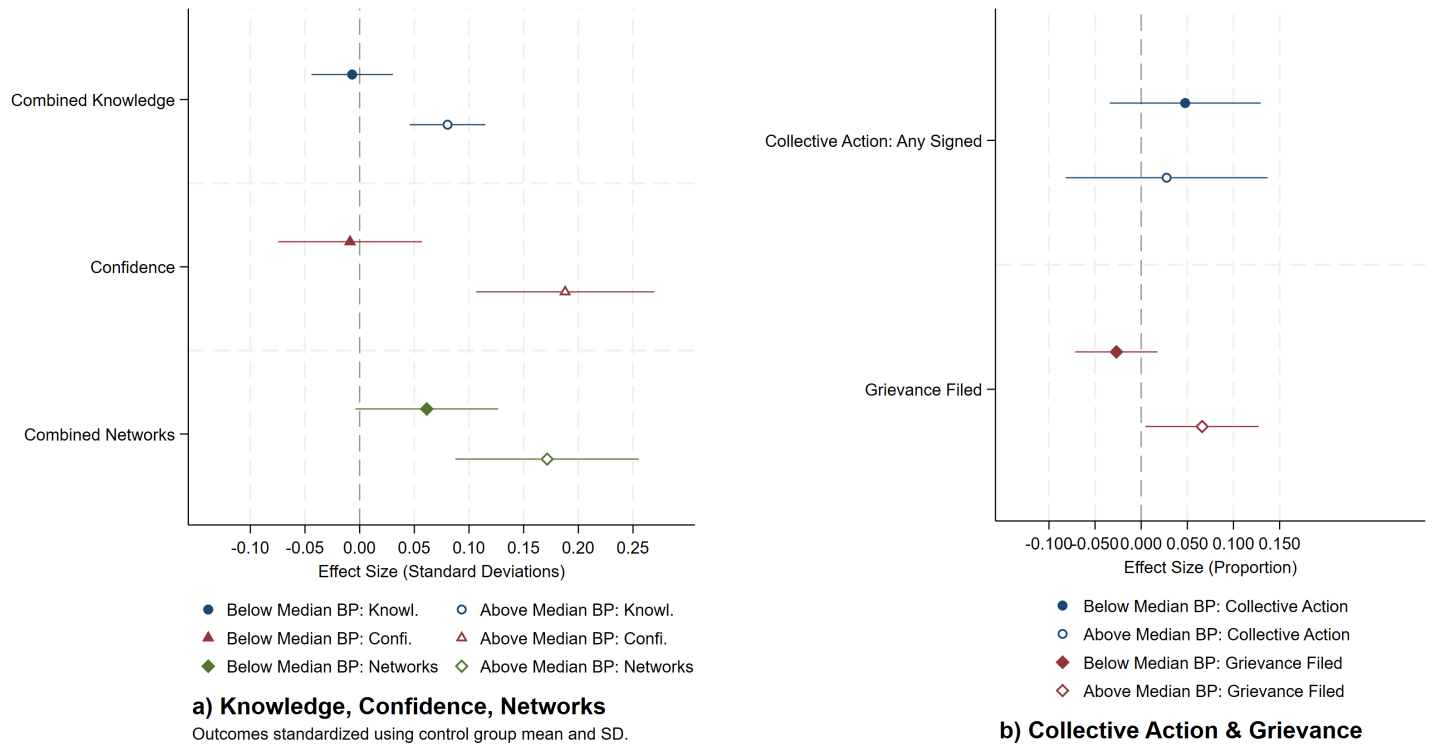
Notes: The above figure gives the histogram of conditional average treatment/spillover effects on combined knowledge index for each ward member taken from our endline survey. The CATE are estimated using the causal forest method of [Wager and Athey \(2018\)](#) and is predicted using individual and group characteristics including knowledge, confidence, interest, training, seclusion, political experience, education, religion, caste, networks, occupation, income and age taken from our baseline survey. Figure (a) to the left plots the predicted values that are estimated using treatment wards and figure (b) to the right plots the predicted values that are estimated using spillover wards.

Figure 5. Treatment Effect on Estimated Cost based on Issues Campaigned and Citizen Preferences



Notes: The above figure shows the treatment effect on estimated costs of planned projects in a GP on each scheme based on the number of WMs campaigned and the number of citizens preferring the scheme within a GP. Estimates on estimated cost for each scheme's project was taken from administrative data collected by the ministry of rural governance in Bihar. Measures on issues campaigned on were taken from the baseline survey and citizen preferences were measured in the citizen survey conducted along the endline survey. In figure a), the first bar to the left represents the sum of the coefficients of the treatment GP and the interaction term between the dummy for treatment GP and the dummy for GPs where no WM campaigned for a scheme in that GP, the second bar represents the sum of coefficients from a separate regression that regresses estimated cost on the interaction term between the treatment dummy and the dummy that flags schemes in which the maximum number of WM campaigned in that GP (along with each covariate added separately in the regression). The schemes used here are Subsidy on House construction (Pradhan Mantri Awas Yojana, PMAY), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (Nali Gali), Provision of tap water (Nal Jal), Pension, Subsidised food rations (Public Distribution System, PDS), Solar Street Lights and Subsidy on Toilet construction (Swachh Bharat Abhiyan, SBM). In figure b), the first bar to the left shows the sum of the treatment GP coefficient and the interaction term between the treatment GP and the dummy that flags scheme which no citizens in that GP showed preference for. Similarly, the second bar shows, from a separate regression, the sum of the treatment GP coefficient and the interaction of the treatment GP with the dummy that flags schemes for which the highest number of citizens showed preference for in that GP. Treated GP refers to those GPs which consist of wards from which elected representatives were selected to participate in the peer groups treatment. The schemes used are Subsidy on House construction (Pradhan Mantri Awas Yojana, PMAY), Health insurance (Ayushman Card), Water conservation (Jal Jeevan Hariyali, JJH), Marriage assistance (Mukhyamantri Kanya Vivah Yojana, MKVY), Public grievance redressal (Lok Shikayat), Solid and liquid waste management (Lohiya Swachh Bharat Abhiyan, LSBA), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (Nali Gali), Provision of tap water (Nal Jal), Subsidised food rations (Public Distribution System, PDS), Solar Street Lights, Entrepreneurship support (Mukhyamantri Udyami Yojana), Subsidy on Toilet construction (Swachh Bharat Abhiyan, SBM), Education, Healthcare, Pension, Subsidised food rations (Public Distribution System, PDS) and Educational financial assistance (Scholarship). Each of the four regressions control for total population (2011 census) and the distance from the nearest town (controls determined using double select lasso) and include district and scheme fixed effects. Standard errors are clustered at the UGP level. The increase/decrease in estimated cost for each case is given in absolute values. Error bars show 90% confidence intervals.

Figure 6. Treatment Heterogeneity in various outcomes: Above Median Best Practices



Notes: The above coefficient plots show the different treatment effects for WMs who were in groups where above median best practices (BP) were discussed compared to WMs who were in groups where below median best practices (BP) were discussed in the meetings for outcomes on combined knowledge index, agency and networks. Combined knowledge index is determined by taking the mean of formal, tacit, procedural and best practices index from our endline survey and standardizing them using the control mean for each scheme. Appendix G.1 further details the construction of each knowledge outcome shown in the table and the schemes used for each index. Outcomes on agency include confidence (measured using the confidence index that is developed using questions from the endline survey, refer to table F7 in the appendix for details), ability to collect signatures for petition (using a dummy that flags WM who were able to attain any signature for the petition used, as reported in the collective action sub-experiment endline survey) and the initiative to file grievances (measured using a dummy that flags WMs who filed a complaint, as reported in the grievance redressal sub-experiment endline survey). Lastly, networks are measured using the combined networks index, which takes the mean of outside GP, bureaucratic block level and political party networks (Reported in the intervention endline survey. Refer to section G.2 of the appendix for more details on each component of the index). Panel A shows the above and below median best practices coefficients for combined knowledge index, confidence index and combined networks index (each outcome here is standardized using the control mean and SD). Figure b) shows the same for collective action and grievance redressal. The regressions in each coefplot regress each outcome on the treatment dummy and a dummy that flags treated WMs who were part of groups where above median best practices were discussed. The regression for knowledge control for baseline characteristics such as knowledge, confidence, education, age, caste, networks as well as on factors such as political experience, availability of mobile communication applications like whatsapp, accessibility to local bureaucrats and politicians, having family in government sector or in politics, WM occupation type, professional relationship with others in panchayat and interest in interacting with other WMs. The regression for networks control for baseline networks at the block, GP and district level, age, years of education, dummies that identify contact access of the ward member to local bureaucrats and political party affiliations of the ward member or a member of their household. Lastly, controls for collective action regression include baseline knowledge and block level networks. Regressions for confidence and grievance redressal are run without controls. For the knowledge regression, which is at the scheme level, we add both district and scheme fixed effects, and control for only district fixed effects in all others. All controls are determined using double select lasso. 90% confidence intervals are used for each coefplot.

B Main Tables

Table 1. Balance across Treatment and Control GPs.

Variable	(1) Control	(2) Treatment	(3) Difference
Proportion of SCs (Census 2011)	0.17 (0.09)	0.17 (0.09)	-0.00 (0.00)
Distance to District Headquarters (Census 2011)	30.27 (13.57)	30.52 (13.68)	0.44 (0.58)
Total GP Area (Census 2011)	1,053.30 (645.29)	1,042.43 (643.75)	-5.61 (25.64)
Total Population of GP (Census 2011)	12,455.46 (5,232.07)	12,426.56 (5,165.76)	25.66 (221.38)
Number of Villages in GP (Census 2011)	5.03 (4.23)	5.10 (4.15)	0.02 (0.15)
Percentages of SCs in Main SC Village (Census 2011)	0.60 (0.25)	0.59 (0.24)	-0.01 (0.01)
SC Reserved	0.17 (0.37)	0.17 (0.38)	0.01 (0.02)
ST Reserved	0.00 (0.06)	0.01 (0.08)	0.00 (0.00)
EBC Reserved	0.17 (0.37)	0.18 (0.38)	0.01 (0.02)
Gender Reserved	0.44 (0.50)	0.46 (0.50)	0.02 (0.02)
Total Educational Facilities (Census 2001)	3.47 (2.04)	3.46 (1.97)	-0.03 (0.08)
Primary Health Sub Centres (Census 2001)	0.44 (0.70)	0.40 (0.66)	-0.04 (0.03)
Post Office (Census 2001)	1.07 (0.81)	1.08 (0.81)	0.01 (0.03)
Bank Facilities (Census 2001)	0.34 (0.63)	0.35 (0.65)	0.02 (0.03)
Power Supply (Census 2001)	1.80 (1.86)	1.76 (1.94)	-0.04 (0.08)
Paved Road (Census 2001)	1.76 (1.63)	1.73 (1.62)	-0.04 (0.07)
Mud Road (Census 2001)	4.10 (3.10)	4.14 (3.10)	0.03 (0.12)
Child Welfare Centre (Census 2001)	0.05 (0.55)	0.04 (0.29)	-0.02 (0.02)
Bus facilities (Census 2001)	0.51 (0.91)	0.54 (0.95)	0.03 (0.04)
Mean Village Income (Census 2001)	415,342.97 (4,826,905.50)	366,579.09 (3,172,319.50)	-42,466.25 (168,499.31)
Mean Village Expenditure (Census 2001)	928,866.12 (21,157,700.00)	255,508.78 (2,111,171.25)	-629,090.56 (552,296.69)
Observations	1,301	912	2,213

Notes: This table displays balance for baseline characteristics between treatment (column 2) and control (column 1) GPs from the experiment. The first five rows of the table show estimates for GP level outcomes taken from the 2011 census. Rows 6 to 9 show outcomes on proportion of reserved seats for different demographics within a GP. Rows 10 to 16 show proportions for availability of different facilities within a GP. The last two rows show mean values for village income and expenditure in a GP. Column (3) provides difference in means after adjusting for district level fixed effects for each outcome. Figures in parenthesis denote robust standard errors. P-values are signified using: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. Effect of Treatment on Knowledge Outcomes

	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Knowledge Index (std)
Treatment Ward	0.04 (0.03)	0.07** (0.03)	0.14*** (0.03)	0.10*** (0.03)	0.13*** (0.03)
Observations	4415	4415	4415	4415	4415
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: This table reports the main treatment effect on different knowledge outcomes from our endline survey of ward members. Column (1) shows knowledges with respect to formal knowledge, determined using questions on formal steps for scheme implementation given in manuals and detailed by bureaucrats. Column (2) shows knowledge with respect to tacit or informal knowledge which is gauged by asking WMs about informal practices involved in the implementation of a scheme. Column (3) shows the outcome for procedural knowledge that tests the WM knowledge on scheme implementation rules. Lastly, column (4) shows the WM knowledge on strategic know-how and problem solving. Column (5) takes the mean of all indices developed from columns (1) to (4) to develop a combined index. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. All indices are standardised using the control mean. Appendix G.1 further details the construction of each knowledge outcome shown in the table. Controls for each regression are determined using double select lasso and include baseline knowledge, confidence, education, age and dummies that control for access to local bureaucrats and connectivity through phone. All regressions control for district fixed effects. Standard errors are reported in parentheses and are clustered at the UGP level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. **Spillover Effects on Knowledge Outcomes**

	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Knowledge Index (std)
Spillover Ward	0.04 (0.03)	0.04 (0.03)	0.09** (0.04)	0.10*** (0.03)	0.08** (0.04)
Observations	4012	4012	3266	4012	4012
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: This table reports the spillover effect on different knowledge outcomes from our endline survey of ward members. Column (1) shows knowledge with respect to formal knowledge, determined using questions on formal steps for scheme implementation given in manuals. Column (2) shows knowledge with respect to tacit or informal knowledge which is gauged by asking WMs about informal practices involved in the implementation of a scheme. Column (3) shows the outcome for procedural knowledge that tests the WM knowledge on scheme implementation rules. Lastly, column (4) shows the WM knowledge on strategic know-how and problem solving. Column (5) takes the mean of all indices developed from columns 1 to 4 to develop a combined index. All indices are standardised using the control mean. A spillover ward is a ward belonging to the survey sample that is part of the treatment GP but has not participated in any peer group meetings. Appendix G.1 further details the construction of each knowledge outcome shown in the table. Controls are determined using double select lasso and include baseline knowledge, confidence, education, age and dummies that control for access to local bureaucrats. District fixed effects are included. Standard errors are reported in parentheses and are clustered at the UGP level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Effect of Treatment on Confidence, Collective Action, and Grievance Redressal

	Confidence	Collective Action		Grievance Redressal
	(1) Confidence Index (std)	(2) Any Signed	(3) Any WM Signed	(4) Grievance Filed
Treatment Ward	0.09*** (0.03)	0.08** (0.04)	0.06* (0.04)	0.01 (0.02)
Observations	4413	619	618	492
WM Controls	No	Yes	Yes	No
Ward-Level Controls	No	Yes	Yes	No
District FE	Yes	Yes	Yes	Yes
Control Mean	0	.18	.16	.08

Notes: The above table shows effect of peer groups on Treated WMs for different measures of agency. Column (1) reports the impact of treatment on the confidence index (standardised using the control mean). The confidence index standardizes the raw count of the number of schemes (out of 19) on which the WM reports feeling confident about implementation in our endline survey. Column (2) and (3) show measures from the collective action sub-experiment's survey where a subset of the study sample were encouraged to collectivize and demand for greater devolution of responsibility to WMs. Column (2) flags those WMs who were able to get the petition signed by at least one person (citizen or ward member), Column (3) flags those WMs who were able to get the petition signed by at least one WM. The outcome on column (4) uses the outcome from the grievance redressal sub-experiment's endline survey where WMs were offered the opportunity to file complaints through Bihar's Grievance Redressal Scheme. The outcome flags those WMs who file a grievance. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. Controls for column (2) include baseline knowledge and controls for column (3) include baseline knowledge and WMs' network at the block level. Columns (1) and (4) are run without additional controls. The controls for each regression is determined using double select lasso. All regressions include district fixed effects. Standard errors clustered at the UGP level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Effects of Treatment on Ward Member Networks

	(1) Outside-GP WM Networks (std)	(2) Block-Level Bureaucrat Networks (std)	(3) Pol-Party Network (std)	(4) Combined Networks Index (std)
Treatment Ward	0.15*** (0.04)	0.07** (0.03)	0.05* (0.03)	0.15*** (0.03)
Observations	4408	4408	4392	4408
Ward-Level Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0

Notes: This table reports the main treatment effect of participating in peer group meetings on ward member network outcomes from our endline survey. Column (1) shows the effect of treatment on WM networks outside the GP. This measure takes the mean of dummy for having peers outside the block but within the district, outside the GP but within the block and a dummy that flags WMs who discuss work difficulty with WMs outside the GP. Column (2) shows effect on block level bureaucratic networks. It takes the mean of two dummies that flag if a WM has spoken to the Block Development Officer (BDO) or the Block Panchayati Raj Officer (BPRO) within the last month of the survey. Column (3) looks at the political party networks of the WM. It flags the WM if they are a member of any political party. Column (4) takes the mean of each measure used in each index created and standardizes it with the control mean to give a combined network index. All other outcomes are also standardized using the control group mean and standard deviation. A treatment ward refers to those wards in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. Controls for each regression include baseline networks at the block, GP and district level, age, years of education, dummies that identify contact access of the ward member to local bureaucrats and political party affiliations of the ward member or a member of their household. All controls were determined using double select lasso. Regressions control for district fixed effects. Standard errors clustered at the UGP level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Effect of Treatment on Conflict and Relationships with GP Level Bureaucrats & Politicians

	(1)	(2)	(3)	(4)	(5)
	Conflict PS	Conflict Rozgar Sevak	Conflict GP Head	Bad Relationship GP Head	Regularity in Village Meet
Treated Ward	0.01** (0.01)	0.01** (0.00)	0.01** (0.01)	0.05*** (0.01)	-0.08*** (0.01)
Observations	4663	4663	4663	4641	4346
WM Controls	No	No	No	No	No
Ward Level Controls	No	No	No	No	No
Control Mean	.04	.01	.04	.15	.34

Notes: The above table reports the effect of being in peer group meetings on conflicts and relationships with local bureaucrats and politicians reported by ward members in our endline survey. Columns (1) to (3) show outcomes associated to dummies that flag if WM has had conflict with GP Secretary (PS), GP NREGA Assistant (*Rozgar Sevak*) and the GP Head respectively. The outcome in column (4) flags if the WM reports to have a bad relationship with the GP Head. Column (5) flags if the WM has attended at least four village meetings (*Gram Sabhas*) since Holi (spring festival occurring in March-April) 2023. Refer to appendix section G.4 for details on the construction of each outcome. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. Each regression controls for district fixed effects. The table reports results for each regression without controls, determined using double select lasso. Standard errors are clustered at the UGP level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Effects of Treatment on GPDP Estimated Costs

	GP × Scheme Level		
	(1) Estimated Cost	(2) Estimated Cost	(3) Estimated Cost
Treated GP	16.76** (7.07)	-2.69 (6.29)	-2.11 (6.83)
Prop. WM Campaigned on Scheme j		81.54** (33.46)	
Treated GP × Prop. WM Campaigned on Scheme j		168.19*** (59.78)	
Citizen Share (Pref j)			64.64 (47.81)
Treated GP × Citizen share (pref. j)			246.03*** (82.50)
Observations	41002	41002	37791
GP-Level Controls	Yes	Yes	Yes
Control Mean	557.87	557.87	557.89

Notes: This table reports the effect of peer group meetings on rural development plans' estimated costs (given in thousands of rupees, collected from administrative data published by ministry of rural governance, Bihar) for each scheme at the gram panchayat level. Column (1) reports the direct effect on estimated cost for each scheme. Column (2) reports the effect of treatment on the estimated cost for each scheme's planned activities with heterogeneity for the proportion of WMs in the GP (out of total WMs surveyed) who reported to have campaigned on the scheme (in our baseline survey). Column (3) reports the effect on estimated cost of planned activities for each scheme in a GP with heterogeneity for the share of citizens (out of the total citizens surveyed) in the GP who prefer that the GP Head/WM increase spending on the scheme. Citizen preference binary for each scheme is taken from our endline citizen survey. Treated GP refers to those GPs which consist of wards members assigned to participate in the peer groups treatment. The schemes include Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY), Health insurance (*Ayushman Card*), Water conservation (*Jal Jeevan Hariyali*, JJH), Marriage assistance (*Mukhyamantri Kanya Vivah Yojana*, MKVY), Public grievance redressal (*Lok Shikayat*), Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (*Nali Gali*), Provision of tap water (*Nal Jal*), Subsidised food rations (Public Distribution System, PDS), Solar Street Lights, Entrepreneurship support (*Mukhyamantri Udyami Yojana*), Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), Education, Healthcare, Pension and Educational financial assistance (Scholarship) as well as an additional category that clubs all projects that could not be identified to a particular scheme into a group named as "uncategorised". All regressions control for total population (as per 2011 census), distance from nearest town and both district and scheme fixed effects. All additional controls are determined using double select lasso. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. **Treatment Heterogeneity in Knowledge: Scheme-Level Predictions for Meeting Quality**

	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Index (std)
<i>Panel A: Scheme-Level RF (Residualized)</i>					
Treated Ward	0.02 (0.03)	0.02 (0.03)	0.04 (0.03)	0.04* (0.02)	0.03 (0.02)
Above Median Predicted (Scheme RF)	0.05* (0.03)	0.02 (0.03)	0.04 (0.04)	0.04* (0.02)	0.06** (0.02)
<i>Panel B: Scheme-Level LASSO</i>					
Treated Ward	0.00 (0.03)	0.00 (0.03)	0.01 (0.03)	0.05** (0.02)	0.03 (0.02)
Above Median Predicted (LASSO)	0.08** (0.03)	0.05 (0.03)	0.10*** (0.04)	0.01 (0.03)	0.04* (0.03)
Observations	13227	9903	5957	22045	28676
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Scheme Fixed Effects	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: The above table shows the effect of being in peer knowledge groups on knowledge for each scheme using heterogeneity for groups that are predicted to have discussed above median number of best practices. Knowledge outcomes are taken from our endline survey and measures on best practices are determined from our meeting notes data. Column (1) shows knowledge with respect to formal knowledge, determined using questions on formal steps for scheme implementation given in manuals and detailed by bureaucrats. Column (2) shows knowledge with respect to tacit or informal knowledge which is gauged by asking WMs about informal practices involved in the implementation of a scheme. Column (3) shows the outcome for procedural knowledge that tests the WM knowledge on scheme implementation rules. Lastly, column (4) shows the WM knowledge on strategic know-how and problem solving. Column (5) takes the mean of all indices developed from columns (1) to (4) to develop a combined index. A treatment ward refers to those wards in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. All indices are standardised using the control mean. Section C.1 further details the construction of each knowledge outcome shown in the table and the schemes used for each index. Panel A shows the heterogeneity in treatment by WMs belonging to groups predicted to have above median best practices. Best practices discussed by each group are predicted using baseline characteristics with random forest of 2,000 trees (minimum node size of 15). Panel B shows heterogeneity in treatment by groups with predicted above median practices. Here, best practices were predicted using baseline characteristics with cross-validated LASSO. All predictions are made on residualised values of best practices after we partial out district and scheme fixed effects. Each regression controls for gender, age, caste, education, district, block and GP level networks and baseline knowledge along with district and scheme fixed effects. Standard errors are clustered at the UGP level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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C Appendix Tables

Table A1. **Ward Members' belief on schemes where they are primarily responsible**

Scheme	Percent of Cases
Drains and Lanes	63.26%
Tap Water	54.39%
Housing	21.29%
Don't know	18.03%
Toilet	16.34%
Pension	15.61%
Solar Lights	12.98%
Sat Nischay	10.58%
NREGA	9.03%
PDS	8.72%
Monitoring development work	8.55%
Conflict resolution support	1.19%
Other schemes	0.92%

The table report the percentage of all surveyed ward members from the baseline survey who identify the ward member as the primary person responsible for the specified issue/scheme. The schemes mentioned are Drains and lanes construction (*Nali Gali*), Provision of tap water (*Nal Jal*), Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY), Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), Pension, Solar street lights, Seven Schemes Guarantee, Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Subsidised food rations (Public Distribution System, PDS) and on issues such as monitoring development work, conflict resolution support respectively.

Table A2. Percentage of Surveyed Citizens Who Perceive Ward Member as the Contact for Scheme-Related Help

	(1)	(2)	(3)	(4)	(5)
	Tap Water	Education	PDS	NREGA	Housing
Percent of Citizens	64.17	14.47	19.07	28.76	33.35
Observations	3581	9699	4766	4764	4929

The above table reports the percentage of all surveyed citizens (from the citizen survey) who identify the Ward Member as their primary help contact for the specified scheme.

The schemes mentioned here include Provision of tap water (*Nal Jal*), Education, Subsidised food rations (Public Distribution System, PDS), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA) and Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY) respectively.

Table A3. **Distribution of Procedural Knowledge Shares for Each Scheme**

	Mean	SD	P10	P25	Median	P75	P90
Accounts	0.51	0.29	0.00	0.33	0.50	0.67	0.83
Housing	0.39	0.19	0.20	0.20	0.40	0.60	0.60
Drains and Lanes	0.20	0.22	0.00	0.00	0.11	0.33	0.44
Tap Water	0.10	0.16	0.00	0.00	0.00	0.20	0.40
PDS	0.73	0.34	0.00	0.50	0.75	1.00	1.00
Pension	0.51	0.25	0.14	0.43	0.57	0.71	0.71
Solar Lights	0.38	0.27	0.00	0.20	0.40	0.60	0.80
All Schemes (Mean)	0.40	0.16	0.18	0.28	0.40	0.51	0.61

Notes: The above table shows the mean and percentile distribution for the share of procedural knowledge steps known by ward members for each scheme/issue, taken from the baseline survey. Shares are normalized by the maximum number of steps observed for that scheme/issue. The schemes/issues included are on accounts, Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY), Drains and lanes construction (*Nali Gali*), Provision of tap water (*Nal Jal*), Subsidised food rations (Public Distribution System, PDS), Pension, Solar street lights and the share for knowledge across all schemes respectively.

Table A4. Districtwise GP Counts and Sampling Strategy

District	GP Sampling	Total GPs	Control GP	Treatment GP
Banka	85% of GPs within a 55 KM radius	139	79	60
Darbhangha	85% of GPs within a 55 KM radius	228	132	96
Gaya	85% of GPs within a 55 KM radius	234	138	96
Jehanabad	85% of GPs within a 55 KM radius	75	39	36
Madhubani	85% of GPs within a 55 KM radius	262	154	108
Muzaffarpur	85% of GPs within a 55 KM radius	296	120	176
Purbi Champaran	85% of GPs within a 55 KM radius	282	174	108
Purnia	85% of GPs within a 55 KM radius	156	96	60
Samastipur	82% of GPs with no distance threshold	280	160	120
Saran	85% of GPs within a 55 KM radius	261	153	108
Total		2213	1245	968

Note: This table describes the GP sampling strategy for each district in our sample (col 2) and the counts for total GPs (col 3), control GPs (col 4) and treated GPs (col 5).

Table A5. District-wise Wards per GP and Sampling Strategy

District	Ward Sampling	Total Wards	Control per GP	Treated per GP	Spillover per GP
Banka	4 T/C wards per GP	678	4	4	2
Darbhangha	2 T/C wards per GP	649	2	2	2
Gaya	4 T/C wards per GP	1,125	4	4	2
Jehanabad	4 T/C wards per GP	374	4	4	2
Madhubani	2 T/C wards per GP	742	2	2	2
Muzaffarpur	2 T/C wards per GP	832	2	2	2
Purbi Champaran	4 T/C wards per GP	1,347	4	4	2
Purnia	2 T/C wards per GP	434	2	2	2
Samastipur	2 T/C wards per GP	800	2	2	2
Saran	2 T/C wards per GP	738	2	2	2
TOTAL		7719	3460	2424	1835

Note: This table describes the (i) sampling frame (Column 2) for all 10 districts in the sample and the number of wards across treatment, control and spillover GPs in our sample (Columns 3 to 6).

Table A6. Balance across Treatment, Control and Spillover Wards (1)

Variable	(1) Control	(2) Treatment	(3) Spillover	(4) T vs C	(5) S vs C
Ward Population	811.84 (179.01)	811.35 (207.82)	810.37 (174.30)	4.95 (8.26)	5.87 (6.37)
Ward SC Population	181.73 (186.31)	190.07 (237.12)	177.60 (209.93)	11.45 (7.97)	9.25 (6.99)
Votes Obtained	153.88 (59.25)	151.85 (58.74)	152.71 (57.57)	-1.34 (2.21)	0.65 (1.90)
Tot. Candidates	4.72 (1.91)	4.72 (1.84)	4.63 (1.89)	-0.01 (0.07)	-0.01 (0.06)
Age	38.96 (11.35)	38.40 (11.37)	39.28 (11.85)	-0.16 (0.39)	0.12 (0.36)
SC	0.33 (0.47)	0.33 (0.47)	0.32 (0.47)	0.02 (0.02)	-0.00 (0.02)
Hindu	0.88 (0.33)	0.89 (0.31)	0.86 (0.34)	0.01 (0.01)	-0.01 (0.01)
Muslim	0.12 (0.32)	0.11 (0.31)	0.13 (0.34)	-0.01 (0.01)	0.01 (0.01)
Years of Education	10.22 (3.96)	10.29 (3.84)	10.19 (4.02)	-0.03 (0.14)	-0.04 (0.13)
<i>Campaigned:</i>	0.83	0.82	0.82	-0.00	0.00
Drains and lanes	(0.38)	(0.38)	(0.39)	(0.01)	(0.01)
<i>Campaigned:</i> Tap water	0.55 (0.50)	0.52 (0.50)	0.52 (0.50)	-0.01 (0.02)	-0.03* (0.02)
<i>Campaigned:</i> Pension	0.18 (0.39)	0.20 (0.40)	0.20 (0.40)	0.00 (0.01)	0.01 (0.01)
<i>Campaigned:</i> Housing	0.27 (0.44)	0.28 (0.45)	0.29 (0.45)	-0.03* (0.02)	0.00 (0.01)
Prev. Experience	0.32 (0.46)	0.31 (0.46)	0.32 (0.47)	-0.00 (0.02)	-0.00 (0.01)
Prev. Experience (Family)	0.10 (0.30)	0.10 (0.30)	0.09 (0.28)	0.00 (0.01)	-0.01 (0.01)
<i>Income Source:</i> Agriculture	0.33 (0.47)	0.37 (0.48)	0.33 (0.47)	0.02 (0.02)	0.01 (0.01)
Received training	0.92 (0.27)	0.93 (0.26)	0.92 (0.28)	0.01 (0.01)	-0.01 (0.01)
Observations	3,460	2,424	1,835	5,884	5,295

Notes: This table displays the balance across Treatment, Control and Spillover samples across administrative and baseline survey data. The first nine rows display the mean values and balance for ward level demographic variables. The variables with the prefix *Campaigned* indicate variables that are based on responses to questions asking what issues WMs campaigned on. “Prev. Experience” indicates if the WM/their family has prior experience being a WM. All regressions have district FE. Errors are clustered at the GP level. P values: * 0.1 ** 0.05 *** 0.01.

Table A7. **Balance across Treatment, Control and Spillover Wards (2)**

Variable	(1) Control	(2) Treatment	(3) Spillover	(4) T vs C	(5) S vs C
<i>Knowledge:</i>	0.39	0.38	0.39	-0.01	0.01
Housing	(0.19)	(0.18)	(0.19)	(0.01)	(0.01)
<i>Knowledge:</i>	0.20	0.20	0.21	-0.01	0.00
Drains/Lanes	(0.22)	(0.21)	(0.22)	(0.01)	(0.01)
<i>Knowledge: Tap</i>	0.11	0.11	0.09	0.00	-0.01
Water	(0.17)	(0.15)	(0.16)	(0.01)	(0.01)
<i>Knowledge: PDS</i>	0.73	0.70	0.74	0.02	-0.00
	(0.34)	(0.34)	(0.34)	(0.02)	(0.02)
<i>Knowledge:</i>	0.50	0.52	0.52	0.03	0.01
Pension	(0.25)	(0.27)	(0.25)	(0.02)	(0.01)
<i>Knowledge:</i>	0.38	0.39	0.38	-0.02*	-0.00
Solar Lights	(0.27)	(0.28)	(0.27)	(0.01)	(0.01)
<i>Knowledge Index</i>	0.04	-0.10	0.06	-0.04	0.02
Z Score	(0.99)	(1.00)	(1.01)	(0.03)	(0.03)
<i>Knowledge Index</i>	0.00	-0.03	0.01	0.01	0.01
(PCA)	(1.50)	(1.55)	(1.49)	(0.12)	(0.08)
<i>Networks: Block</i>	0.19	0.23	0.21	0.02	0.01
	(0.44)	(0.49)	(0.47)	(0.02)	(0.01)
<i>Networks: Dist.</i>	0.02	0.02	0.02	0.01	0.00
	(0.15)	(0.15)	(0.15)	(0.01)	(0.00)
<i>Networks: State</i>	0.01	0.00	0.01	0.00	0.00
	(0.09)	(0.07)	(0.08)	(0.00)	(0.00)
<i>Networks: All</i>	0.20	0.24	0.22	0.03	0.01
	(0.49)	(0.53)	(0.52)	(0.02)	(0.02)
Interested in Peer	0.96	0.95	0.94	-0.01	-0.01
Learning	(0.21)	(0.23)	(0.23)	(0.01)	(0.01)
Pol. Party Involvement	0.20	0.21	0.22	-0.01	0.01
	(0.40)	(0.40)	(0.41)	(0.01)	(0.01)
WhatsApp	0.81	0.81	0.81	0.00	0.00
	(0.40)	(0.39)	(0.40)	(0.01)	(0.01)
Observations	3,460	2,424	1,835	5,884	5,295

Notes: This table displays the balance across Treatment, Control and Spillover samples across measures of knowledge and networks from our baseline survey data. The Knowledge Index is a standardized index of WM's knowledge on 6 key schemes, i.e. provision of tap water (*Nal Jal*), subsidy on house construction (*Pradhan Mantri Awas Yojana*, PMAY), drains and lanes construction (*Nali gali*), solar street lights, subsidised food rations (Public Distribution System, PDS) and pensions. We first identify the steps involved in carrying out these schemes. We then calculate the share of the total steps a ward member is able to recount in our survey. We then calculate the PCA score among these variables. Our main network question involves asking ward members to name ward members in their GP/block/district/state who they have work-related discussions. Ward members can name up to 3 such peers. *Networks: All* is the sum of all individuals respondents can name across levels. The variable WhatsApp is a dummy that flags if the WM has access to the application. All regressions have district FE. Errors are clustered at the GP level. P values: * 0.1 ** 0.05 *** 0.01.

Table A8. **Treatment Heterogeneity in Knowledge: Rivalrous and Non-Rivalrous Schemes**

	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Knowledge Index (std)
	Index for each WM at the Scheme level				
Treatment Ward	0.03 (0.02)	0.04* (0.02)	0.02 (0.02)	0.03* (0.02)	0.04** (0.02)
Treatment Ward × Rivalrous scheme	-0.00 (0.03)	-0.02 (0.03)	0.08 (0.06)	0.03 (0.03)	0.03 (0.02)
Observations	17636	14312	10366	26454	33085
WM Controls	Yes	Yes	Yes	Yes	Yes
Cluster	UGP	UGP	UGP	UGP	UGP
Control Mean	0	0	0	0	0

Notes: The above table shows the treatment effects on knowledge for schemes that are categorised as rivalrous compared to schemes that are categorised as non-rivalrous. Column (1) shows knowledges with respect to formal knowledge, determined using questions on formal steps for scheme implementation given in manuals and detailed by bureaucrats. Column (2) shows knowledge with respect to tacit or informal knowledge which is gauged by asking WMs about informal practices involved in the implementation of a scheme. Column (3) shows the outcome for procedural knowledge that tests the WM knowledge on scheme implementation rules. Lastly, column (4) shows the WM knowledge on strategic know-how and problem solving. Column (5) takes the mean of all indices developed from columns (1) to (4) to develop a combined index. All outcomes use variables collected from our endline survey. Appendix G.1 further details the construction of each knowledge outcome shown in the table. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. We define rivalrous schemes as those schemes whose increase in demand made by a ward member for their own ward would affect the supply for the same scheme in another ward. This includes schemes such as Provision of tap water (*Nal Jal*), Drains and lanes construction (*Nali Gali*) and Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA). All other schemes where increase in demand made by a ward member does not affect supply are included as non-rivalrous. This includes Subsidy on House construction (*Pradhan Mantri Awas Yojana, PMAY*), Health insurance (*Ayushman Card*), Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan, LSBA*), Subsidised food rations (Public Distribution System, PDS), Solar Street Lights and Subsidy on Toilet construction (*Swachh Bharat Abhiyan, SBM*). Further details on this classification is given in Appendix C.10. Controls include (determined by double select lasso) baseline knowledge, confidence, education, age, baseline networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, if ward member received training and dummies that control for access to local bureaucrats and connectivity through phone. Regressions control for district and scheme fixed effects. All outcome indices are standardized using the control group mean and standard deviation. Standard errors are clustered at the UGP level and are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9. **Spillover Heterogeneity in Knowledge: Rivalrous and Non-Rivalrous Schemes**

	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Knowledge Index (std)
Index for each WM at the Scheme level					
Spillover Ward	0.02 (0.03)	0.04 (0.03)	0.02 (0.03)	0.07*** (0.02)	0.07*** (0.02)
Spillover Ward X Rivalrous scheme	0.04 (0.03)	-0.01 (0.03)	0.14 (0.09)	-0.05* (0.03)	-0.04 (0.02)
Observations	16184	13096	7718	24276	30311
WM Controls	Yes	Yes	Yes	Yes	Yes
Cluster	UGP	UGP	UGP	UGP	UGP
Control Mean	0	0	0	0	0

Notes: The above table shows the spillover effects on different outcomes of knowledge for schemes that are categorised as rivalrous compared to schemes that are categorised as non-rivalrous. Column (1) shows knowledges with respect to formal knowledge, determined using questions on formal steps for scheme implementation given in manuals and detailed by bureaucrats. Column (2) shows knowledge with respect to tacit or informal knowledge which is gauged by asking WMs about informal practices involved in the implementation of a scheme. Column (3) shows the outcome for procedural knowledge that tests the WM knowledge on scheme implementation rules. Lastly, column (4) shows the WM knowledge on strategic know-how and problem solving. Column (5) takes the mean of all indices developed from columns (1) to (4) to develop a combined index. All outcomes are developed using variables from our endline survey. Appendix G.1 further details the construction of each knowledge outcome shown in the table. A spillover ward is defined as a ward that is not a treated ward but lies within a treated GP. We define rivalrous schemes as those schemes whose increase in demand made by a ward member for their own ward would affect the supply for the same scheme in another ward. This includes schemes such as Provision of tap water (*Nal Jal*), Drains and lanes construction (*Nali Gali*) and Work provided under employment guarantee (*National Rural Employment Guarantee Act, NREGA*). All other schemes where increase in demand made by a ward member does not affect supply are included as non-rivalrous. This includes Subsidy on House construction (*Pradhan Mantri Awas Yojana, PMAY*), Health insurance (*Ayushman Card*), Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan, LSBA*), Subsidised food rations (Public Distribution System, PDS), Solar Street Lights and Subsidy on Toilet construction (*Swachh Bharat Abhiyan, SBM*). Further details on this classification is given in Appendix G.10. Controls include (determined by double select lasso) baseline knowledge, confidence, education, age, baseline networks, caste, controls for political and bureaucratic affiliation, past experience, interest in study participation, if ward member received training and dummies that control for access to local bureaucrats and connectivity through phone. Regressions control for district and scheme fixed effects. All outcome indices are standardized using the control group mean and standard deviation. Standard errors are clustered at the UGP level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10. **Spillover Effects on Combined Knowledge Index by Social and Political Affiliation**

	Index for each WM at Scheme level		
	(1) Caste	(2) Religion	(3) Political Party
<i>Caste</i>			
WM Count: Treated Ward & same caste in GP	0.04** (0.02)		
WM Count: Treated Ward & diff. caste in GP	0.02* (0.01)		
<i>Religion</i>			
WM Count: Treated Ward & same religion in GP		0.03*** (0.01)	
WM Count: Treated Ward & diff. religion in GP		0.02 (0.02)	
<i>Political party affiliation</i>			
WM Count: Treated Ward & same party in GP			0.17** (0.07)
WM Count: Treated Ward & diff. party in GP			-0.05 (0.05)
WM Count: Treated Ward & no political party in GP			0.03*** (0.01)
p-val (diff. in coeff.)	0.271	0.775	0.045
Observations	30311	30311	30311
WM level controls	Yes	Yes	Yes
Ward level controls	Yes	Yes	Yes
Cluster	UGP	UGP	UGP
Control mean	0	0	0

Notes: The table reports spillover effects on the overall knowledge index by social and political affiliation. Column (1) shows spillover effects by the count of treated ward members who belong to the same or different caste as the ward member in a GP. Column (2) shows spillover effects by the count of treated ward members who belong to the same or different religion as the ward member in a GP. Column (3) shows spillover effects by political party affiliation, distinguishing between treated ward members who share the same party, belong to a different party, or report no political party involvement. All indices are standardised using the control mean. The combined knowledge index takes the average of all standardized indices and is standardized using the control mean. Controls include baseline knowledge, confidence, education, age, baseline networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, if ward member received training and dummies that control for access to local bureaucrats and connectivity through phone. All regressions control for district and scheme fixed effects. Standard errors are clustered at the UGP level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11. Effect of Treatment on Within-Group Knowledge Variance

	(1) Combined Knowledge Index (Variance)	(2) Combined Knowledge Index (Variance)
Treatment Group	0.14*** (0.04)	0.14*** (0.04)
Baseline Knowledge Variance	-0.01 (0.05)	-0.01 (0.05)
Observations	498	498
Controls	No	Yes

The above table shows the effect of treatment on the variation in knowledge within a peer group. Combined knowledge index is determined by taking the mean of formal, tacit, procedural and best practices index from our endline survey and standardizing them using the control mean for each scheme for each ward member. Appendix C.1 further details the construction of each knowledge outcome shown in the table and the schemes used for each index. All ward members, including those in controls in our sample were randomly assigned to groups. Hence, ward members who participated in peer group meetings were in treated groups whereas ward members assigned to control were also allotted to "fictitious groups". Baseline knowledge index is determined using knowledge outcomes recorded at baseline. All specifications include district fixed effects. Column (1) regression is run without controls. Controls in column (2) include: Caste, age, woman, education, and networks. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12. **Impact of Treatment on Collective Action: Number of Signatures**

	No.Signed
Treatment Ward	0.43* (0.25)
Observations	619
WM Controls	Yes
Ward-Level Controls	Yes
District FE	Yes
Control Mean	.33

Notes: This table reports the effect of treatment on number of signatures collected in the petition as part of the collective action sub-experiment. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. Controls include baseline knowledge and block level networks of the ward member (determined using double select lasso). District fixed effects included. Standard errors clustered at the UGP level are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13. Effects of Treatment on GPDP Estimated Costs (excluding uncategorized schemes)

	GP × Scheme Level		
	(1) Estimated Cost	(2) Estimated Cost	(3) Estimated Cost
Treated GP	19.94*** (6.40)	0.69 (9.24)	1.07 (5.03)
Prop. WM Campaigned on Scheme j		94.77*** (33.76)	
Treated GP × Prop. WM Campaigned on Scheme j		163.56*** (62.62)	
Citizen Share (Pref j)			67.61 (47.67)
Treated GP × Citizen share (pref. j)			238.66*** (81.18)
Observations	38844	19359	35802
GP-Level Controls	Yes	Yes	Yes
Control Mean	371.46	371.46	372.05

Notes: This table reports the effect of peer group meetings on rural development plans' estimated costs (given in thousands of rupees, collected from administrative data published by ministry of rural governance, Bihar) for each scheme at the gram panchayat level. Column (1) reports the direct effect on estimated cost for each scheme. Column (2) reports the effect of treatment on the estimated cost for each scheme's planned activities with heterogeneity for the proportion of WMs in the GP (out of total WMs surveyed) who reported to have campaigned on the scheme (in our baseline survey). Column (3) reports the effect on estimated cost of planned activities for each scheme in a GP with heterogeneity for the share of citizens (out of the total citizens surveyed) in the GP who prefer that the GP Head/WM increase spending on the scheme. Citizen preference binary for each scheme is taken from our endline citizen survey. Treated GP refers to those GPs which consist of wards members assigned to participate in the peer groups treatment. The schemes include Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY), Health insurance (*Ayushman Card*), Water conservation (*Jal Jeevan Hariyali*, JJH), Marriage assistance (*Mukhyamantri Kanya Vivah Yojana*, MKVY), Public grievance redressal (*Lok Shikayat*), Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (*Nali Gali*), Provision of tap water (*Nal Jal*), Subsidised food rations (Public Distribution System, PDS), Solar Street Lights, Entrepreneurship support (*Mukhyamantri Udyami Yojana*), Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), Education, Healthcare, Pension, Subsidised food rations (Public Distribution System, PDS) and Educational financial assistance (Scholarship). Column (2) regresses estimated cost only on the 8 schemes for which information on issues campaigned on was recorded. These are Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (*Nali Gali*), Provision of tap water (*Nal Jal*), Subsidised food rations (Public Distribution System, PDS), Solar Street Lights, Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), Pension, Subsidised food rations (Public Distribution System, PDS). All regressions control for total population (as per 2011 census), distance from nearest town and both district and scheme fixed effects. All additional controls are determined using double select lasso. Robust standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14. **Treatment effects on Estimated Cost with Heterogeneity on GP Head Margin of Victory**

	(1) Estimated Cost (₹000s)	(2) Estimated Cost (₹000s)
Treated GP	388.08*** (143.77)	392.55*** (142.79)
Margin of Victory (relative)	219.96 (222.59)	253.14 (222.88)
Treated GP $\times$ MoV (relative)	-651.80* (357.54)	-668.87* (355.31)
Observations	1925	1925
GP-Level Controls	No	Yes
District FE	Yes	Yes
Control Mean	5001.96	5001.96

Notes: This table reports the GP-level treatment effect on rural development plans' estimated costs (given in thousands of rupees, collected from administrative data published by ministry of rural governance, Bihar), along with its interaction with the winning candidate's relative margin of victory, taken from the Bihar's state election commission's data. Estimated cost outcomes are in thousands of rupees. MoV (relative) is the winner's vote margin over the first runner-up, normalized by the average of the two candidates' vote totals. GP-level controls include total population, determined by double select lasso. All regressions control for district fixed effects. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15. Citizen Preferences by Treatment Status

Variable	(1) Control	(2) Treatment	(3) T vs C
Drains and Lanes	0.51 (0.50)	0.53 (0.50)	0.02* (0.01)
Tap Water	0.33 (0.47)	0.34 (0.47)	0.01 (0.01)
PDS	0.03 (0.18)	0.03 (0.17)	-0.00 (0.00)
Pension	0.03 (0.16)	0.02 (0.16)	-0.00 (0.00)
Toilet	0.06 (0.24)	0.06 (0.23)	-0.00 (0.00)
Housing	0.12 (0.33)	0.13 (0.34)	0.01 (0.01)
NREGA	0.22 (0.42)	0.22 (0.42)	-0.00 (0.01)
Solar Lights	0.08 (0.28)	0.09 (0.29)	0.01* (0.01)
SLWM - LSBA	0.05 (0.21)	0.05 (0.21)	0.00 (0.00)
Water Conservation	0.01 (0.09)	0.00 (0.07)	-0.00* (0.00)
Scholarship	0.00 (0.03)	0.00 (0.04)	0.00 (0.00)
RTPS	0.00 (0.04)	0.00 (0.03)	-0.00 (0.00)
Education	0.04 (0.21)	0.04 (0.20)	-0.00 (0.00)
Marriage Assistance	0.00 (0.04)	0.00 (0.05)	0.00 (0.00)
Grievance Redressal	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Health Insurance	0.00 (0.01)	0.00 (0.02)	0.00 (0.00)
Entrepreneurship Support	0.00 (0.05)	0.00 (0.05)	-0.00 (0.00)
Healthcare	0.02 (0.13)	0.02 (0.12)	-0.00 (0.00)
Observations	4,746	4,953	9,699

Notes: The above table shows the balance in citizen preference for different schemes across treatment and control GPs. The schemes used are Drains and lanes construction (*Nali Gali*), Provision of tap water (*Nal Jal*), Subsidised food rations (Public Distribution System, PDS), Pension, Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Solar Street Lights, Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), Water conservation (*Jal Jeevan Hariyali*, JJH), Educational financial assistance (Scholarship) Marriage assistance (*Mukhyamantri Kanya Vivah Yojana*, MKVY), Public grievance redressal (*Lok Shikayat*), Health insurance (*Ayushman Card*), Entrepreneurship support (*Mukhyamantri Udyami Yojana*), and Healthcare respectively. Robust Standard Errors are reported in parantheses. *** p<0.01, ** p<0.05, * p<0.1

Table A16. Treated WMs Better Understand Citizen Preferences (GP $\times$ Scheme)

	(1) Share of Citizens in GP Preferring Scheme j
Share of WMs in GP who think citizens prefer scheme j	0.01 (0.01)
Treated GP $\times$ Share of WMs in GP who think citizens prefer scheme j	0.04*** (0.01)
Observations	36,017
Scheme FE	Yes
District FE	Yes
Cluster	Robust
Controls	No
Control Mean	.08

Notes: The above table shows the effect of treatment on WM's understanding of citizen preferences. Our outcome is the share of citizens in the GP preferring scheme j. Treated GP refers to those GPs which consist of wards members assigned to participate in the peer groups treatment. The regression includes the treated GP covariate, the covariate for the share of WM in the GP who think that citizens prefer scheme j and the interaction of the two covariates. The schemes used are Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY), Health insurance (*Ayushman Card*), Water conservation (*Jal Jeevan Hariyali*, JJH), Marriage assistance (*Mukhyamantri Kanya Vivah Yojana*, MKVY), Public grievance redressal (*Lok Shikayat*), Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSB), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (*Nali Gali*), Provision of tap water (*Nal Jal*), Subsidised food rations (Public Distribution System, PDS), Solar Street Lights, Entrepreneurship support (*Mukhyamantri Udyami Yojana*), Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), Education, Healthcare, Pension, Subsidised food rations (Public Distribution System, PDS) and Educational financial assistance (Scholarship). Regression controls for district and scheme fixed effects. Standard errors are given in parantheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A17. Effects of Treatment on GPDP Planned Projects

	GP $\times$ Scheme Level		
	(1) Projects	(2) Projects	(3) Projects
<i>Panel A: All Schemes (incl. Uncategorized)</i>			
Treated GP	0.05 (0.07)	-0.06 (0.07)	-0.06 (0.07)
Prop. WM Campaigned on Scheme j		2.72*** (0.15)	
Treated GP $\times$ Prop. WM Campaigned on Scheme j		0.98*** (0.25)	
Citizen Share (Pref j)			3.42*** (0.23)
Treated GP $\times$ Citizen Share (Pref. j)			1.42*** (0.36)
Observations	41002	40280	37791
<i>Panel B: Categorized Schemes Only</i>			
Treated GP	0.06** (0.03)	-0.11*** (0.03)	-0.11*** (0.03)
Prop. WM Campaigned on Scheme j		4.51*** (0.05)	
Treated GP $\times$ Prop. WM Campaigned on Scheme j		1.47*** (0.09)	
Citizen Share (Pref j)			5.97*** (0.08)
Treated GP $\times$ Citizen Share (Pref. j)			1.91*** (0.13)
Observations	38844	38160	35802
GP-Level Controls	Yes	Yes	Yes
Scheme FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Control Mean	1.01	1.01	1.01

Notes: This table reports the effects of treatment for each scheme in a GP on planned projects reported in the administrative data of the ministry of rural governance, Bihar. *Panel A* includes all activities, including those not categorized under any scheme. *Panel B* restricts to categorized schemes only. Column (1) shows effect of treatment with no heterogeneity; column (2) shows heterogeneity by the proportion of WMs who campaigned on scheme j (schemes campaigned on by WM were reported in our baseline survey); column (3) shows heterogeneity by the share of citizens preferring scheme j (citizen preferences were measured in our citizen survey). Treated GP refers to those GPs which consist of wards members assigned to participate in the peer groups treatment. GP-level controls include total population, number of villages, total area, distance from district headquarters, distance from nearest town, and proportion of SC population, determined by double select lasso. All columns control for scheme and district fixed effects. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A18. Effects of Treatment on GPDP Estimated Costs – Heterogeneity by WM Campaign and Citizen Preference Extremes

	GP × Scheme Level			
	(1) Estimated Cost	(2) Estimated Cost	(3) Estimated Cost	(4) Estimated Cost
Treated GP	59.80** (26.38)	27.18*** (9.59)	71.74*** (26.44)	11.55** (4.89)
No WM Campaigned on Scheme j	-1.54 (17.20)			
Treated GP × No WM Campaigned on Scheme j	-36.94 (28.37)			
Most WMs Campaigned on Scheme j		10.16 (28.83)		
Treated GP × Most WMs Campaigned on Scheme j		102.69* (54.72)		
No Citizen Preferred Scheme j			-6.97 (16.82)	
Treated GP × No Citizen Preferred Scheme j			-67.44** (27.13)	
Most Citizens Preferred Scheme j				-11.76 (22.44)
Treated GP × Most Citizens Preferred Scheme j				115.05** (46.77)
Observations	17264	17264	35802	35802
GP-Level Controls	Yes	Yes	Yes	Yes
Control Mean	372.05	372.05	372.05	372.05

Notes: This table shows the treatment effect on estimated costs of planned projects in a GP on each scheme depending on the number of WMs campaigned and the number of citizens preferring the scheme within a GP. Estimates on estimated cost for each scheme project was taken from administrative data collected by the ministry of rural governance in Bihar. Measures on issues campaigned on were taken from the baseline survey and citizen preferences were measured in the citizen survey conducted at endline. Column (1) and (2) show heterogeneity in treatment effects on estimated cost by i) schemes that no one campaigned on, ii) schemes that were the most campaigned on. The dummies for i) and ii) were made using questions on the number of issues campaigned asked during the baseline survey. Columns (3) and (4) show heterogeneity in treatment effects on estimated cost by iii) schemes that no citizen preferred and iv) schemes that most citizens preferred. The dummies for iii) and iv) were made using questions asked on citizen preferences for schemes in the citizen survey at endline. Treated GP refers to those GPs which consist of wards members assigned to participate in the peer groups treatment. The schemes used are Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY), Health insurance (*Ayushman Card*), Water conservation (*Jal Jeevan Hariyali*, JJH), Marriage assistance (*Mukhyamantri Kanya Vivah Yojana*, MKVY), Public grievance redressal (*Lok Shikayat*), Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (*Nali Gali*), Provision of tap water (*Nal Jal*), Subsidised food rations (Public Distribution System, PDS), Solar Street Lights, Entrepreneurship support (*Mukhyamantri Udyami Yojana*), Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), Education, Healthcare, Pension, Subsidised food rations (*Public Distribution System*, PDS) and Educational financial assistance (Scholarship). Each of the four regressions control for total population (2011 census) and the distance from the nearest town and include district and scheme fixed effects. Controls are determined using double select lasso. Standard errors clustered at the UGP level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A19. Effects of Treated Wards on Citizen Reports of Public Goods and Welfare Programs

	(1)	(2)	(3)	(4)	(5)	
	Tap Water (Std)	Drains and Lanes (Std)	Solar Lights (Std)	SLWM - LSBA (Std)	Combined Public Good Index (std)	
Panel A: Public Goods						
Treated Wards	0.06* (0.03)	0.01 (0.03)	-0.02 (0.03)	-0.05* (0.03)	-0.00 (0.02)	
Observations	4216	4192	4105	4127	8322	
Ward, Citi., HH Controls	No	No	No	No	No	
Cluster	Ward	Ward	Ward	Ward	Ward	
Control Mean	0	0	0	0	0	
	Job Card (Std)	PDS (Std)	Pension (Std)	Toilet (Std)	Housing (Std)	Combined Welfare Index (std)
Panel B: Welfare Programs						
Treated Wards	-0.01 (0.03)	0.04 (0.03)	0.02 (0.03)	-0.02 (0.03)	0.02 (0.03)	0.02 (0.02)
Observations	4103	4085	5521	4160	4203	8320
Ward, Citi., HH Controls	No	No	No	No	No	No
Cluster	Ward	Ward	Ward	Ward	Ward	Ward
Control Mean	0	0	0	0	0	0

Notes: The above table reports the effect of ward member peer group meetings on the application and receipt of government program benefits as reported by citizens in the citizen survey. Panel A reports the effect of treatment on the application or receipt of public goods. Panel B reports the same for welfare programs. Each column in both panels represents an outcome that flags the application or receipt of a particular scheme by a citizen and standardizes it using the control mean. The last column of each panel takes the row mean of all preceding columns and standardizing it again using the control mean - creating a combined index. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. Panel A, from columns (1) to (4) represent schemes Provision of tap water (*Nal Jal*), Drains and lanes construction (*Nali Gali*), Solar street lights and Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA) respectively. Panel B, from columns (1) to (5) represent the application for job card as part of Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Subsidised food rations (Public Distribution System, PDS), Pension, Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM) and Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY) respectively. Regressions are run with district fixed effects and no controls. Determination of controls was done using double select lasso. Standard errors are clustered at the ward level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20. **Summary of Projects by Scheme**

	Projects Sampled	Projects Located	Location Rate (%)
Drains and lanes	51	23	45.1
NREGA	67	31	46.3
Solar Lights	27	22	81.5
Tap water	4	1	25.0
Total Projects	149	77	51.7

Notes: The above table summarises all the projects sampled and located in the GPDP audit survey by scheme. Column (1) reports the number of projects sampled under each scheme in the survey. Column (2) reports the number of those sampled projects that were located on the ground. Column (3) reports the location rate - the share of sampled projects that were located (Column (2) divided by Column (1)). The last row gives us the sum total of projects sampled, the projects located and the rate of location. The schemes included are Drains and lanes construction (*Nali Gali*), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Solar street lights and Provision of tap water (*Nal Jal*)

Table A21. **Ward Member Involvement in Completed Projects, by Scheme**

	Ward Member Role (%)	Total Projects
Drains and lanes	47.4	19
NREGA	11.5	26
Solar Lights	66.7	15
Tap water	0.0	1
Total	36.1	61

Notes: The table reports the percentage of completed projects that were found under each scheme in which the ward member was attributed a role in project implementation as part of the audit survey. The Total row reports the share across all schemes. Column (2) gives the total number of completed projects that were found for each scheme. The schemes included here are Drains and lanes construction (*Nali Gali*), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Solar Street Lights and Provision of tap water (*Nal Jal*) respectively.

Table A22. Effect of Treatment on Citizen Rating & Perception

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Vote for WM in Future	WM Wins Next Election	Satisfaction with WM Work	WM Public Image	WM-Block Coordination	WM-GP Head Coordination	Combined Perception Index
Treated Ward	-0.00 (0.02)	0.02 (0.02)	0.01 (0.02)	0.02 (0.02)	-0.03 (0.03)	-0.01 (0.02)	0.01 (0.02)
Observations	7109	7556	8225	8158	6307	7387	8316
WM Controls	No	No	No	No	No	No	No
Ward Level Controls	No	No	No	No	No	No	No
Control Mean	0.48	2.82	2.91	3.48	3.11	3.27	0.00

Notes: The above table reports the effect of treatment on citizen ratings and perception. All outcomes are rated on a Likert scale by citizens in the citizen survey and is later standardized using the control group mean and standard deviation. The final column reports results for a combined index constructed as the mean of the six standardized outcomes, re-standardized using the control group mean and standard deviation. A treatment ward refers to those wards where the ward representative in the survey sample is part of the treatment GP and has been exposed to peer group meetings. Each regression controls for district fixed effects. Results are reported without additional controls. Standard errors are clustered at the ward level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A23. **Main Actor Responsible for Completed Projects, by Scheme**

Person Responsible	Drains and lanes (%)	NREGA (%)	Solar Lights (%)	Tap water (%)
Ward Member	5.3	3.8	60.0	0.0
GP Head	78.9	61.5	13.3	0.0
GP Secretary	5.3	3.8	6.7	0.0
Contractor/Dealer	0.0	3.8	0.0	0.0
Don't Know/ Don't Remember	0.0	7.7	0.0	0.0
Others	10.5	15.4	0.0	0.0
No Main Person	0.0	3.8	20.0	100.0

Notes: The table shows, for each scheme, the share of projects attributed to different local actors as recorded in the audit survey. In this table, we only take into account the person who was attributed as the main person responsible. There are a total of 61 completed projects that were found with 5 projects having no one person as the person having main responsibility. The schemes included here are Drains and lanes construction (*Nali Gali*), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Solar Street Lights and Provision of tap water (*Nal Jal*) respectively.

Table A24. Treatment Effects on Self-Dealing and Citizen Reports of Bribe

	(1) Day-Share Year 23-25	(2) Day-Share Year 24-25	(3) If Worked Year 23-25	(4) If Worked Year 24-25	(5) Day-Count Year 23-25	(6) Day-Count Year 24-25
<i>Panel A: Self-Dealing</i>						
Treated GP	0.00 (0.00)	0.00 (0.00)				
Treated Ward			0.00 (0.01)	-0.00 (0.01)	-3.02 (3.12)	-1.55 (1.78)
Observations	1506	1506	5551	5551	887	906
Controls	No	No	Ward	Ward	Ward	Ward
Cluster	Robust	Robust	UGP	UGP	UGP	UGP
Control Mean	0	0	.08	.06	34.87	16.07
	NREGA	Ration Card	Pension	Toilet	Housing	Combined Index (Std)
<i>Panel B: Citizen Reports of Bribe Taken</i>						
Treated Wards	0.00 (0.01)	-0.02* (0.01)	0.01 (0.01)	0.02 (0.02)	0.04** (0.02)	0.04 (0.03)
Observations	891	823	1203	895	855	3650
Controls	No	No	No	No	No	No
Cluster	Ward	Ward	Ward	Ward	Ward	Ward
Control Mean	.02	.03	.04	.08	.04	0

Notes: The above table reports the effect of Treatment on different measures of corruption. Panel A presents treatment effects on self-dealing measures taken from administration data provided by the government of India for Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA). Self-dealing refers to ward members assigning more days worked to own household. Hence, an increase in the share or count of days worked by ward members is considered an increase in self-dealing of days worked by ward members. Columns (1) and (2) show effects on the share of NREGA days worked by ward members within their GP for 2023-2025 and 2024-2025 respectively, with GP-level controls and robust standard errors. Columns (3) and (4) show effects on a binary indicator for having worked at all, and Columns (5) and (6) show effects on total day counts, both with ward-level controls and standard errors clustered at the GP level. Panel B reports treatment effects on citizen reports (in the citizen survey) of bribes taken by ward members for various schemes, with ward-level controls and standard errors clustered at the Ward level. The schemes included from columns (1) to (5) are Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), availment of a ration card as part of Subsidised food rations (Public Distribution System, PDS), Pension, Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM) and Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY) respectively. Column (6) takes the row mean of each binary outcome from columns (1) to (5) and standardizes it using the control mean. A treatment ward refers to those wards in the survey sample that are part of the treatment GP and has the ward member exposed to peer group meetings. Treated GP refers to those GPs which were randomly assigned to have wards members selected to participate in the peer groups treatment. GP level regressions in panel A are run with no controls. Ward controls include baseline knowledge, networks, confidence and past experience of ward members. No controls are added to panel B regression. This is determined using double select lasso method. All regressions control for district fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A25. **Treatment Effects on NREGA Outcomes**

	(1) Total Person Days	(2) Total HH Worked	(3) SC Person Days	(4) Women Person Days
<i>Panel A: Year 2024–2025</i>				
Treated GP	-196.63 (642.70)	-1.20 (10.41)	-109.70 (213.08)	-230.98 (372.34)
Observations	2171	2171	2171	2171
Control Mean	28138.93	590.69	5810.19	16009.26
<i>Panel B: Year 2023-2024</i>				
Treated GP	-737.93 (597.90)	-3.98 (10.34)	-100.20 (189.42)	-537.00 (345.68)
Observations	2156	2156	2156	2156
GP Controls	Yes	Yes	Yes	Yes
Pre-period Controls	Yes	Yes	Yes	Yes
Control Mean	25834.11	565	5229.82	14542.1

Notes: The above table shows the effect of being in Treated GP on NREGA outcomes (taken from the national level administrative data collected as part of the National Rural Employment Guarantee Act by the ministry of rural development, India). Panel A shows estimates for period 2024–2025 and Panel B for 2023-2024. Column (1), (3) and (4) show effects of belonging to treatment GP on person days in total, for SC and women respectively. Column (2) shows effect of belonging to treatment GP on total households worked. Treated GP refers to those GPs which consist of wards members assigned to participate in the peer groups treatment. We control for average person days of pre-period in each panel as well as for district fixed effects. Controls include (determined by double select lasso) total population of the GP, number of villages, total area, distance from district HQ, distance from nearest town and proportion of SC citizens in the GP. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A26. Treatment Effects Without Baseline Controls

	(1) Combined Knowledge Index (std)	(2) Combined Knowledge Index (std)	(3) Confidence Index (std)	(4) Networks Index (std)	(5) Projects	(6) Estimated Cost
Treatment Ward	0.10*** (0.03)		0.09*** (0.03)	0.17*** (0.03)		
Spillover Ward		0.10*** (0.04)				
Treated GP					0.77** (0.32)	231.75*** (82.94)
Observations	4663	4259	4413	4663	2158	2158
WM level Controls	No	No	No	No	No	No
GP level Controls	No	No	No	No	No	No
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	UGP	UGP	UGP	UGP	Robust	Robust
Control Mean	0	0	0	0	14.49	5001.96

Notes: The above table shows the effects of Treatment/Spillover on different outcomes without baseline controls. Column (1) shows the effect of treatment at the ward level on the combined knowledge index determined using outcomes from our endline ward member survey. Column (2) shows the same for spillover wards. Combined knowledge index is determined by taking the mean of formal, tacit, procedural and best practices index (taken from the endline survey) and standardizing them using the control mean. Details on the composition of formal, tacit, procedural and best practices index are given in [G.1](#). Column (3) reports the impact of treatment at the ward level on the confidence index (standardised using the control mean). The confidence index standardizes the raw count of the number of schemes (out of 19) on which the WM reports feeling confident about implementation in our endline survey. Column (4) reports the impact of treatment on the combined networks index, determined using outside GP WM networks, block bureaucratic networks and political party networks. Refer to section [G.2](#) for details on the composition of the networks index. Column (5) reports the effect of treatment at the GP level on the number of projects planned as per the gram panchayat development program, collected from administrative data published by ministry of rural governance, Bihar. Column (6) reports the effects on estimated cost. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. Treated GP refers to those GPs which consist of wards members assigned to participate in the peer groups treatment. All regressions control for district fixed effects and indices are standardized using the control mean (columns (1) to (4)). Standard errors are clustered at the GP level for columns (1) to (4). Robust standard errors are reported in parentheses for columns (5) and (6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A27. Treatment Effects with Standard Errors Clustered at the Peer-Group Level.

	(1) Combined Knowledge Index (std)	(2) Confidence Index (std)	(3) Networks Index (std)
Treatment Ward	0.12*** (0.03)	0.10*** (0.03)	0.16*** (0.04)
Observations	4300	4072	4300
WM level Controls	No	No	No
District Fixed Effects	Yes	Yes	Yes
Cluster	Group	Group	Group
Control Mean	0	0	0

The above table reports the effect of treatment at the ward level on knowledge, confidence and network outcomes with standard errors clustered at the peer group level. Column (1) shows the effect of treatment at the ward level on the combined knowledge index determined using outcomes from our endline ward member survey. Combined knowledge index is determined by taking the mean of formal, tacit, procedural and best practices index (taken from the endline survey) and standardizing them using the control mean. Details on the composition of formal, tacit, procedural and best practices index are given in [G.1](#). Column (2) reports the impact of treatment at the ward level on the confidence index (standardised using the control mean). The confidence index standardizes the raw count of the number of schemes (out of 19) on which the WM reports feeling confident about implementation in our endline survey. Column (3) reports the impact of treatment on the combined networks index, determined using outside GP WM networks, block bureaucratic networks and political party networks. Refer to section [G.2](#) for details on the composition of the networks index. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. All regressions control for district fixed effects and indices are standardized using the control mean. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A28. **Learning and Best-Practice Exchange Using a Leave-Own-Out Exposure Measure**

	Index for each WM at the Scheme level				
	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Knowledge Index (std)
Panel A: Best Practices					
Treated Ward	-0.01 (0.03)	0.03 (0.03)	0.02 (0.03)	0.02 (0.02)	0.02 (0.02)
Above Median Best Practices	0.06** (0.03)	0.01 (0.03)	0.03 (0.03)	0.04** (0.02)	0.05** (0.02)
Observations	17636	14312	10366	26454	33085
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Scheme Fixed Effects	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: This table examines heterogeneity in treatment effects by meeting quality where meeting quality is a pure exposure measure. Column (1) shows knowledges with respect to formal knowledge, determined using questions on formal steps for scheme implementation given in manuals and detailed by bureaucrats. Column (2) shows knowledge with respect to tacit or informal knowledge which is gauged by asking WMs about informal practices involved in the implementation of a scheme. Column (3) shows the outcome for procedural knowledge that tests the WM knowledge on scheme implementation rules. Lastly, column (4) shows the WM knowledge on strategic know-how and problem solving. Column (5) takes the mean of all indices developed from columns (1) to (4) to develop a combined index. Section G.1 further details the construction of each knowledge outcome shown in the table and the schemes used for each index. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. A treated ward member is classified as having above median best practices if the total number of best practices discussed (reported in meeting notes) in their group exceeds the median best practices across all groups. In case of leave-own-out, we remove any best practices that were suggested by the ward member themselves. All indices are standardised using the control mean. Controls are determined using double select lasso and include baseline knowledge, confidence, education, age, baseline networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, training received, and dummies for access to local bureaucrats. District and scheme fixed effects are included. Standard errors are reported in parentheses and are clustered at the UGP level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A29. **Balance Table: Baseline Characteristics by Endline Survey Status**

Variable	(1) Found	(2) Not Found	(3) Found vs Not Found
Ward population	812.984 (190.493)	804.135 (175.672)	8.546 (6.025)
SC Population	186.029 (214.178)	167.924 (184.321)	18.018*** (6.623)
Votes Obtained	153.801 (59.092)	148.979 (57.043)	5.199*** (1.930)
Tot. Candidates	4.695 (1.883)	4.761 (1.879)	-0.050 (0.061)
Age	38.897 (11.380)	38.133 (11.355)	0.748** (0.361)
SC	0.332 (0.471)	0.295 (0.456)	0.038*** (0.014)
Hindu	0.881 (0.323)	0.867 (0.340)	0.015 (0.010)
Muslim	0.116 (0.320)	0.128 (0.335)	-0.013 (0.010)
Years of Education	10.174 (3.886)	10.531 (4.154)	-0.400*** (0.129)
<i>Camp</i> : Drains and lanes	0.824 (0.381)	0.813 (0.390)	0.013 (0.012)
<i>Camp</i> : Tap water	0.525 (0.499)	0.559 (0.497)	-0.028* (0.015)
<i>Camp</i> : Pension	0.193 (0.394)	0.177 (0.382)	0.010 (0.012)
<i>Camp</i> : Housing	0.286 (0.452)	0.238 (0.426)	0.042*** (0.013)
Prev. Experience	0.321 (0.467)	0.285 (0.452)	0.040*** (0.014)
Ever WM before, from family	0.100 (0.301)	0.090 (0.286)	0.010 (0.009)
<i>Income Source</i> : Agriculture	0.343 (0.475)	0.339 (0.473)	0.003 (0.015)
Received training	0.924 (0.266)	0.909 (0.287)	0.014 (0.009)
Treated Ward	0.315 (0.464)	0.326 (0.469)	-0.027** (0.012)
Control Ward	0.436 (0.496)	0.495 (0.500)	-0.051*** (0.014)
Spillover Ward	0.249 (0.433)	0.179 (0.383)	0.079*** (0.012)
Observations	6,213	1,246	7,459

Notes: This table compares baseline characteristics between surveyed wards members who were found (and surveyed) at endline vs those who were not. Column (1) reports means for wards members who were found at endline, column (2) for ward members who were not found at endline, and column (3) reports the differences in means. Rows 1 to 9 show the balance for different demographic features. Rows 10 to 13 show the proportions of WM that campaigned for different schemes. Row 14 shows balance for past experience of ward members and row 15 shows balance for past experience (if any) of family members. Standard errors clustered at the GP level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A30. **Balance Table: Baseline Characteristics by Endline Survey Status (2)**

Variable	(1) Found	(2) Not Found	(3) Found vs Not Found
<i>Knowledge: Housing</i>	0.388 (0.189)	0.380 (0.188)	0.007 (0.006)
<i>Knowledge: Drains and lanes</i>	0.203 (0.215)	0.184 (0.216)	0.017** (0.007)
<i>Knowledge: Tap water</i>	0.108 (0.163)	0.090 (0.154)	0.014 (0.009)
<i>Knowledge: PDS</i>	0.736 (0.335)	0.690 (0.348)	0.053*** (0.017)
<i>Knowledge: Pension</i>	0.519 (0.252)	0.478 (0.255)	0.041*** (0.013)
<i>Knowledge: Solar Lights</i>	0.387 (0.270)	0.364 (0.268)	0.019** (0.009)
<i>Knowledge index</i>	0.015 (1.000)	-0.072 (0.998)	0.097*** (0.031)
<i>Knowledge Index: PCA</i>	0.058 (1.492)	-0.265 (1.525)	0.318*** (0.087)
<i>Baseline block peer network</i>	0.216 (0.478)	0.157 (0.405)	0.054*** (0.013)
<i>Baseline district peer network</i>	0.023 (0.157)	0.015 (0.129)	0.007* (0.004)
<i>Networks: State</i>	0.006 (0.088)	0.000 (0.000)	0.006*** (0.001)
<i>Networks: All</i>	0.245 (0.540)	0.172 (0.440)	0.067*** (0.014)
<i>Interested in Peer Learning</i>	0.952 (0.213)	0.936 (0.245)	0.015** (0.007)
<i>Involvement in the political party</i>	0.214 (0.410)	0.181 (0.385)	0.031** (0.012)
<i>WhatsApp</i>	0.809 (0.393)	0.796 (0.403)	0.010 (0.012)
<i>Treated Ward</i>	0.315 (0.464)	0.326 (0.469)	-0.027** (0.012)
<i>Control Ward</i>	0.436 (0.496)	0.495 (0.500)	-0.051*** (0.014)
<i>Spillover Ward</i>	0.249 (0.433)	0.179 (0.383)	0.079*** (0.012)
Observations	6,213	1,246	7,459

Notes: This table compares baseline characteristics between wards members who were found at endline vs those who were not. Column (1) reports means for wards members who were found at endline, column (2) for ward members who were not found at endline, and column (3) reports differences in means. Rows 1 to 6 show the balance for the percentage of steps known by WM of each group for different scheme implementation. Rows 11 to 14 show balance for different network outcomes. Row 15 shows balance for interest in participation in peer groups. Row 16 shows balance for political party participation and row 15 shows balance for having access to Whatsapp. Standard errors clustered at the GP level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A31. Balance Across Treatment Status: Conditional on WM found at Endline

Variable	(1) Control	(2) Treatment	(3) Spillover	(4) T vs C	(5) S vs C
Ward population	813.709 (180.153)	813.108 (214.507)	811.601 (175.610)	0.722 (6.994)	2.403 (6.670)
SC Population	184.075 (185.454)	193.647 (248.155)	179.975 (214.104)	8.271 (7.531)	5.310 (7.535)
Votes Obtained	154.600 (59.388)	152.674 (59.660)	153.789 (57.844)	-1.598 (1.928)	0.474 (1.998)
Tot. Candidates	4.721 (1.898)	4.728 (1.845)	4.607 (1.903)	0.029 (0.060)	-0.035 (0.065)
Age	38.967 (11.313)	38.536 (11.218)	39.231 (11.695)	-0.438 (0.336)	-0.039 (0.382)
SC	0.330 (0.470)	0.344 (0.475)	0.321 (0.467)	0.014 (0.014)	-0.012 (0.016)
Hindu	0.880 (0.324)	0.895 (0.306)	0.866 (0.341)	0.010 (0.010)	-0.013 (0.011)
Muslim	0.117 (0.322)	0.102 (0.302)	0.132 (0.338)	-0.011 (0.010)	0.012 (0.011)
Years of Education	10.182 (3.889)	10.204 (3.801)	10.122 (3.987)	-0.001 (0.117)	-0.054 (0.133)
<i>Camp</i> : Drains and lanes	0.835 (0.372)	0.819 (0.385)	0.813 (0.390)	-0.017 (0.011)	-0.014 (0.013)
<i>Camp</i> : Tap water	0.549 (0.498)	0.505 (0.500)	0.510 (0.500)	-0.045*** (0.015)	-0.042*** (0.016)
<i>Camp</i> : Pension; Old age, CM pension	0.181 (0.385)	0.202 (0.402)	0.201 (0.401)	0.022* (0.012)	0.011 (0.013)
<i>Camp</i> : Housing	0.281 (0.449)	0.282 (0.450)	0.298 (0.458)	0.006 (0.013)	0.002 (0.015)
Prev. Experience	0.319 (0.466)	0.325 (0.469)	0.318 (0.466)	0.007 (0.014)	-0.009 (0.016)
Ever WM before, from family	0.107 (0.309)	0.103 (0.304)	0.087 (0.282)	-0.004 (0.009)	-0.019* (0.010)
<i>Income Source</i> :	0.337 (0.473)	0.366 (0.482)	0.326 (0.469)	0.032** (0.015)	-0.005 (0.015)
Agriculture	0.923 (0.267)	0.927 (0.260)	0.920 (0.271)	0.004 (0.008)	-0.010 (0.009)
Received training					
Observations	2,709	1,954	1,550	4,663	4,259

Notes: This table displays the balance across Treatment, Control and Spillover samples (conditional on WM being found at endline) across administrative and baseline survey data. Rows 1 to 9 show the balance for different demographic features. Rows 10 to 13 show the proportions of WM that campaigned for different schemes. Row 14 shows balance for past experience of ward members and row 15 shows balance for past experience (if any) of family members. Standard errors are clustered at the GP level in parentheses. All regressions have district FE. P val-ues: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A32. **Balance Across Treatment Status: Conditional on WM found at Endline (2)**

Variable	(1) Control	(2) Treatment	(3) Spillover	(4) T vs C	(5) S vs C
<i>Knowledge: Housing</i>	0.392 (0.193)	0.379 (0.182)	0.394 (0.193)	-0.012** (0.006)	0.000 (0.006)
<i>Knowledge: Drains and lanes</i>	0.199 (0.216)	0.202 (0.210)	0.209 (0.220)	0.004 (0.007)	0.003 (0.008)
<i>Knowledge: Tap water</i>	0.112 (0.168)	0.108 (0.149)	0.097 (0.157)	0.006 (0.012)	-0.008 (0.009)
<i>Knowledge: PDS</i>	0.739 (0.330)	0.717 (0.342)	0.741 (0.344)	0.000 (0.020)	-0.003 (0.017)
<i>Knowledge: Pension</i>	0.514 (0.246)	0.532 (0.270)	0.518 (0.253)	0.024 (0.015)	0.002 (0.013)
<i>Knowledge: Solar Lights</i>	0.390 (0.265)	0.391 (0.276)	0.376 (0.271)	0.003 (0.009)	-0.014 (0.009)
Scheme steps Knowledge Index z-score	-0.016 (0.975)	0.004 (1.007)	0.022 (1.033)	0.019 (0.030)	0.049 (0.033)
<i>Knowledge Index (PCA)</i>	0.077 (1.474)	0.050 (1.551)	0.021 (1.496)	0.069 (0.116)	-0.030 (0.084)
Baseline block peer network	0.203 (0.457)	0.236 (0.500)	0.213 (0.485)	0.035** (0.015)	0.001 (0.015)
Baseline district peer network	0.021 (0.158)	0.024 (0.156)	0.024 (0.158)	0.003 (0.005)	0.001 (0.005)
<i>Networks: State</i>	0.006 (0.098)	0.006 (0.076)	0.006 (0.085)	-0.001 (0.003)	-0.001 (0.003)
<i>Networks: All</i>	0.230 (0.525)	0.266 (0.551)	0.243 (0.551)	0.037** (0.016)	0.001 (0.018)
Interested in Peer Learning	0.958 (0.201)	0.950 (0.218)	0.945 (0.228)	-0.007 (0.006)	-0.009 (0.007)
Involvement in the political party	0.210 (0.408)	0.211 (0.408)	0.222 (0.416)	0.001 (0.012)	0.009 (0.014)
WhatsApp	0.809 (0.393)	0.815 (0.389)	0.803 (0.398)	0.008 (0.012)	0.001 (0.013)
Observations	2,709	1,954	1,550	4,663	4,259

Notes: This table displays the balance across Treatment, Control and Spillover samples (conditional on WM being found at endline) across administrative and baseline survey data. Rows 5 to 7 show measures on knowledge for specific schemes for different treatment groups. Rows 1 to 6 show the balance for the percentage of steps known by WM of each group for different scheme implementation. Rows 9 to 12 show balance for different network outcomes. Row 13 shows balance for interest in participation in peer groups. Row 14 shows balance for political party participation and row 15 shows balance for having access to Whatsapp. All regressions have district FE. Errors are clustered at the GP level. P values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A33. Attrition-adjusted treatment effects (doubly robust estimator)

Outcome	Treatment effect	(SE)	N
Combined knowledge index	0.07***	(0.03)	4663
Confidence Index	0.09**	(0.04)	4413
Professional Networks Index	0.08***	(0.02)	4663
Bad Relationship with GP Head	0.04***	(0.01)	4641

Notes: The above table reports the doubly robust (augmented inverse probability weighting [AIPW]) estimates of the treatment effect for different ward member level outcomes. The first row shows the attrition adjusted treatment effect for combined knowledge index. Combined knowledge index is determined by taking the mean of formal, tacit, procedural and best practices index (taken from the endline survey) and standardizing them using the control mean. Details on the composition of formal, tacit, procedural and best practices index are given in [G.1](#). The second row shows the adjusted estimates for the confidence index. The confidence index standardizes the raw count of the number of schemes (out of 19) on which the WM reports feeling confident about implementation in our endline survey. The third row shows the estimates for the combined network index determined using outside GP WM networks, block bureaucratic networks and political party networks. Refer to section [G.2](#) for details on the composition of the networks index. The last row shows the adjusted treatment effect for the dummy flagging ward members who reported to have a bad relationship with the GP head - an indicator for conflict. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. The N here refers to the total number of treatment and control wards included for the estimation. Standard errors are clustered at the GP level (UGP) and obtained via 500 cluster bootstrap replications. All models condition on baseline covariates and district fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A34. Attrition-adjusted spillover effects (doubly robust estimator)

Outcome	Spillover effect	(SE)	N
Combined knowledge index	0.03*	(0.02)	4259
Confidence Index	0.01	(0.03)	4014
Professional Networks Index	-0.01	(0.02)	3593
Bad Relationship with GP Head	0.01	(0.01)	4240

Notes: The above table reports the doubly robust (augmented inverse probability weighting [AIPW]) estimates of the spillover effect for different ward member level outcomes. The first row shows the attrition adjusted treatment effect for combined knowledge index. Combined knowledge index is determined by taking the mean of formal, tacit, procedural and best practices index (taken from the endline survey) and standardizing them using the control mean. Details on the composition of formal, tacit, procedural and best practices index are given in [G.1](#). The second row shows the adjusted estimates for the confidence index. The confidence index standardizes the raw count of the number of schemes (out of 19) on which the WM reports feeling confident about implementation in our endline survey. The third row shows the estimates for the combined network index determined using outside GP WM networks, block bureaucratic networks and political party networks. Refer to section [G.2](#) for details on the composition of the networks index. The last row shows the adjusted treatment effect for the dummy flagging ward members who reported to have a bad relationship with the GP head - an indicator for conflict. . A spillover ward is a ward belonging to the survey sample that is part of the treatment GP but has not participated in any peer group meetings. The N here refers to the total number of spillover and control wards included for the estimation. Standard errors are clustered at the GP level (UGP) and obtained via 500 cluster bootstrap replications. All models condition on baseline covariates and district fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A35. **Lee bounds for endline attrition with predicted-response stratification (Lee 2009 §4)**

Outcome	Trim	Lower (SE)	Upper (SE)	IM 95% CI	N
<i>Treatment vs Control</i>					
Combined knowledge index	2.87%	0.06** (0.02)	0.10*** (0.02)	[0.02, 0.14]	5,884
Confidence Index	4.55%	0.01 (0.04)	0.09** (0.04)	[-0.07, 0.15]	5,884
Professional Networks Index	2.87%	0.05*** (0.02)	0.08*** (0.02)	[0.02, 0.11]	5,884
Bad Relationship with GP Head	2.89%	0.03*** (0.01)	0.04*** (0.02)	[0.01, 0.07]	5,884
<i>Spillover vs Control</i>					
Combined knowledge index	7.31%	0.00 (0.04)	0.04 (0.04)	[-0.07, 0.11]	5,295

Notes: The above table gives us the lee bound treatment and spillover estimates for the combined knowledge, confidence, networks index and the dummy for conflict/relationship (with GP Head). For the panel with treatment and control sample, the first row shows the attrition adjusted treatment effect for combined knowledge index. Combined knowledge index is determined by taking the mean of formal, tacit, procedural and best practices index (taken from the endline survey) and standardizing them using the control mean. Details on the composition of formal, tacit, procedural and best practices index are given in [G.1](#). The second row shows the adjusted estimates for the confidence index. The confidence index standardizes the raw count of the number of schemes (out of 19) on which the WM reports feeling confident about implementation in our endline survey. The third row shows the estimates for the combined network index determined using outside GP WM networks, block bureaucratic networks and political party networks. Refer to section [G.2](#) for details on the composition of the networks index. The last row shows the adjusted treatment effect for the dummy flagging ward members who reported to have a bad relationship with the GP head - an indicator for conflict. For the panel with spillover and control sample, the table reports the lee bound estimates for combined knowledge index. A treatment ward refers to those ward members in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. A spillover ward is a ward belonging to the survey sample that is part of the treatment GP but has not participated in any peer group meetings. Lee (2009) bounds are tightened within two strata of predicted response probability, above and below the median (Lee 2009 §4) in columns 3 and 4 respectively. The trim is equal to the differential attrition divided by the larger response rate. Standard errors in parentheses come from a cluster bootstrap at the GP level. IM 95% CI is the Imbens-Manski confidence interval for the treatment-effect parameter. The last column reports the sample used to estimate the bounds (treatment and control wards for first panel, spillover and control for second). Stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A36. **Best Practices Discussed by Scheme**

Scheme	No. of Best Practices		
	10th Percentile	Mean	90th Percentile
Tap water	2.00	4.43	6.82
Drains and lanes	0.00	1.52	3.14
NREGA	0.00	1.72	3.56
Pension	0.00	0.63	1.73
Toilet	0.62	2.15	4.00
PDS	0.00	1.50	3.11
Housing	0.78	2.44	4.50
Solar Lights	0.00	1.59	3.27
SLWM - LSBA	1.56	3.37	5.36
RTPS	0.00	0.17	0.80
Total	0.00	1.95	4.37

Notes: This table summarizes, for each scheme, the number of best practices (solutions) discussed during peer meetings. Ward-level averages and 10th/90th percentiles are first computed by scheme, then averaged across wards to produce the values shown. The schemes included here are Provision of tap water (*Nal Jal*), Drains and lanes construction (*Nali Gali*), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Pension, Subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), Subsidised food rations (Public Distribution System, PDS), Subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY), Solar street lights, Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA) and Public service delivery (Right to Public Services, RTPS) respectively. The Total row pools all scheme-ward observations together.

Table A37. Treatment Heterogeneity in Knowledge: Above Median Best Practices

	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Knowledge Index (std)
Index for each WM at the Scheme level					
Treatment Ward	-0.04 (0.03)	0.01 (0.03)	0.01 (0.03)	-0.01 (0.02)	-0.01 (0.02)
Treat x Above Median Best Practices	0.09*** (0.03)	0.03 (0.03)	0.03 (0.03)	0.07*** (0.02)	0.08*** (0.02)
Observations	17636	14312	10366	26454	33085
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Scheme FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: This table examines heterogeneity in treatment effects by meeting quality on knowledge using our endline ward member survey. Column (1) shows knowledges with respect to formal knowledge, determined using questions on formal steps for scheme implementation given in manuals and detailed by bureaucrats. Column (2) shows knowledge with respect to tacit or informal knowledge which is gauged by asking WMs about informal practices involved in the implementation of a scheme. Column (3) shows the outcome for procedural knowledge that tests the WM knowledge on scheme implementation rules. Lastly, column (4) shows the WM knowledge on strategic know-how and problem solving. Column (5) takes the mean of all indices developed from columns (1) to (4) to develop a combined index. Section G.1 further details the construction of each knowledge outcome shown in the table and the schemes used for each index. A treatment ward refers to those wards in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. A treated ward member is classified as having above median best practices if the total number of best practices discussed (reported in meeting notes) in their group exceeds the median best practices across all groups. All indices are standardised using the control mean. Controls are determined using double select lasso and include baseline knowledge, confidence, education, age, baseline networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, training received, and dummies for access to local bureaucrats. District and scheme fixed effects are included. Standard errors are reported in parentheses and are clustered at the UGP level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A38. **Treatment Heterogeneity in Networks: Above Median Best Practices**

	(1) Outside-GP WM Networks (std)	(2) Block-Level Bureaucrat Networks (std)	(3) Pol-Party Network (std)	(4) Combined Networks Index (std)
Treatment Ward	0.04 (0.04)	0.03 (0.04)	0.03 (0.04)	0.06 (0.04)
Treat $\times$ Above Median Best Practices	0.19*** (0.06)	0.07 (0.05)	0.03 (0.04)	0.17*** (0.05)
Observations	4408	4408	4392	4408
Ward-Level Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0

Notes: This table examines heterogeneity in treatment effects on networks by above median best practices discussed in meetings. Column (1) shows the effect of treatment on WM networks outside the GP. This measure takes the mean of dummy for having peers outside the block but within the district, outside the GP but within the block and a dummy that flags WMs who discuss work difficulty with WMs outside the GP. Column (2) shows effect on block level bureaucratic networks. It takes the mean of two dummies that flag if a WM has spoken to the Block Development Officer (BDO) or the Block Panchayati Raj Officer (BPRO) within the last month of the survey. Column (3) looks at the political party networks of the WM. It flags the WM if they are a member of any political party. Column (4) takes the mean of each measure used in each index created and standardizes it with the control mean to give a combined network index. All other outcomes are also standardized using the control group mean and standard deviation. A treatment ward refers to those wards in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. A treated ward member is classified as having above median best practices if the total number of best practices discussed in their meetings exceeds the median across all meetings. Controls for each regression include baseline networks at the block, GP and district level, age, years of education, dummies that identify contact access of the ward member to local bureaucrats and political party affiliations of the ward member or a member of their household. All controls were determined using double select lasso. Regressions control for district fixed effects. Standard errors clustered at the UGP level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A39. **Treatment Heterogeneity in Confidence, Collective Action, and Grievance Redressal: Above Median Best Practices**

	Confidence Index (std)	Any WM Signed	Any Signed	Grievance Filed
Treatment Ward	-0.01 (0.04)	0.43* (0.25)	0.05 (0.05)	-0.03 (0.03)
Treat × Above Median Best Practices	0.19*** (0.05)		0.03 (0.07)	0.07* (0.04)
Observations	4413	619	618	492
WM Controls	No	Yes	Yes	No
Ward-Level Controls	No	Yes	Yes	No
District FE	Yes	Yes	Yes	Yes
Control Mean	0	.33	.16	.08

Notes: This table examines treatment heterogeneity by above median best practices discussed in meetings for different outcomes for agency. Column (1) reports the impact of treatment on the confidence index (standardised using the control mean). The confidence index standardizes the raw count of the number of schemes (out of 19) on which the WM reports feeling confident about implementation in our endline survey. Column (2) and (3) show measures from the collective action sub-experiment's survey where a subset of the study sample were encouraged to collectivize and demand for greater devolution of responsibility to WMs. Column (2) flags those WMs who were able to get the petition signed by at least one person, Column (3) flags those WMs who were able to get the petition signed by at least one WM. The outcome on column (4) uses the outcome from the grievance redressal sub-experiment's endline survey where WMs were offered the opportunity to file complaints through Bihar's Grievance Redressal Scheme. The outcome flags those WMs who file a grievance. Treatment ward refers to those wards in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. A treated ward member is classified as having above median best practices if the total number of best practices discussed in their meetings exceeds the median across all meeting Controls for column (2) include baseline knowledge and controls for column (3) include baseline knowledge and WMs' network at the block level. Columns (1) and (4) are run without additional controls. The controls for each regression is determined using double select lasso. All regressions include district fixed effects. Standard errors clustered at the UGP level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A40. **Heterogeneity in Knowledge: Above-Median Scheme Discussion (Whatsapp)**

	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Knowledge Index (std)
Treatment Ward	0.03 (0.03)	0.02 (0.03)	0.07** (0.03)	0.04** (0.02)	0.04** (0.02)
Above Median Scheme Texts	0.03 (0.03)	0.01 (0.03)	-0.05 (0.04)	0.03 (0.02)	0.03 (0.02)
Observations	13227	9903	5957	22045	28676
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward Controls	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: This table examines heterogeneity in treatment effects by the number of text messages exchanged by each peer group on different schemes on knowledge using our endline ward member survey. Column (1) shows knowledges with respect to formal knowledge, determined using questions on formal steps for scheme implementation given in manuals and detailed by bureaucrats. Column (2) shows knowledge with respect to tacit or informal knowledge which is gauged by asking WMs about informal practices involved in the implementation of a scheme. Column (3) shows the outcome for procedural knowledge that tests the WM knowledge on scheme implementation rules. Lastly, column (4) shows the WM knowledge on strategic know-how and problem solving. Column (5) takes the mean of all indices developed from columns (1) to (4) to develop a combined index. Section G.1 further details the construction of each knowledge outcome shown in the table and the schemes used for each index. A treatment ward refers to those wards in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. A treated ward member is classified as having above median scheme texts if the total number of texts exchanged about a certain scheme (recorded in whatsapp chat transcripts) in their group exceeds the median number of texts exchanged on the scheme across all groups. All indices are standardised using the control mean. Controls are determined using double select lasso and include baseline knowledge, confidence, education, age, baseline networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, training received, and dummies for access to local bureaucrats. District and scheme fixed effects are included. Standard errors are reported in parentheses and are clustered at the UGP level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

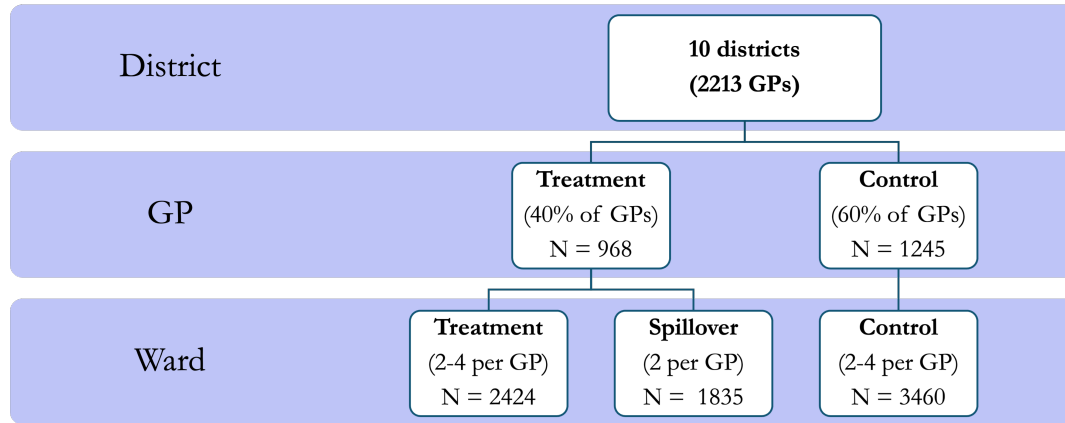
Table A41. Treatment Heterogeneity in Knowledge for Each Scheme - Continuous: Discussion Intensity (on Whatsapp)

	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Knowledge Index (std)
Treatment Ward	0.04*	0.02	0.05**	0.06***	0.05***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Scheme Discussion (per SD)	0.02	0.01	-0.01	0.02*	0.02*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Observations	13227	9903	5957	22045	28676
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward Controls	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: This table examines heterogeneity in treatment effects by the number of text messages exchanged by each peer group on different schemes on knowledge using our endline ward member survey. Here, scheme Discussion is a within-scheme z-score of scheme-specific message counts (direct keyword classification) in the treated WhatsApp group, standardized using the mean and standard deviation among treated groups for each scheme. Column (1) shows knowledges with respect to formal knowledge, determined using questions on formal steps for scheme implementation given in manuals and detailed by bureaucrats. Column (2) shows knowledge with respect to tacit or informal knowledge which is gauged by asking WMs about informal practices involved in the implementation of a scheme. Column (3) shows the outcome for procedural knowledge that tests the WM knowledge on scheme implementation rules. Lastly, column (4) shows the WM knowledge on strategic know-how and problem solving. Column (5) takes the mean of all indices developed from columns (1) to (4) to develop a combined index. Section G.1 further details the construction of each knowledge outcome shown in the table and the schemes used for each index. A treatment ward refers to those wards in the survey sample that are part of the treatment GP and have been exposed to peer group meetings. All indices are standardised using the control mean. Controls are determined using double select lasso and include baseline knowledge, confidence, education, age, baseline networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, training received, and dummies for access to local bureaucrats. District and scheme fixed effects are included. Standard errors are reported in parentheses and are clustered at the UGP level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

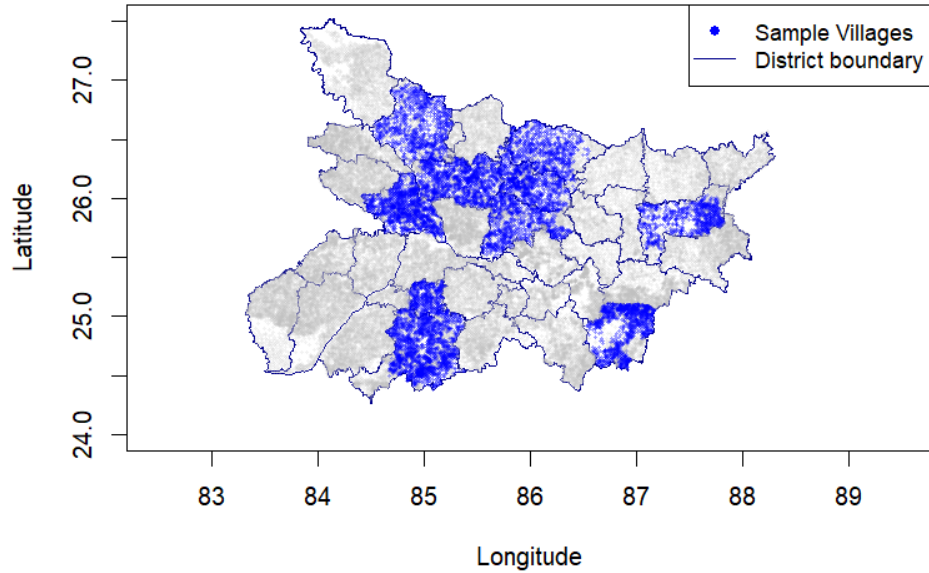
D Appendix Figures

Figure A1. **Sampling Strategy**

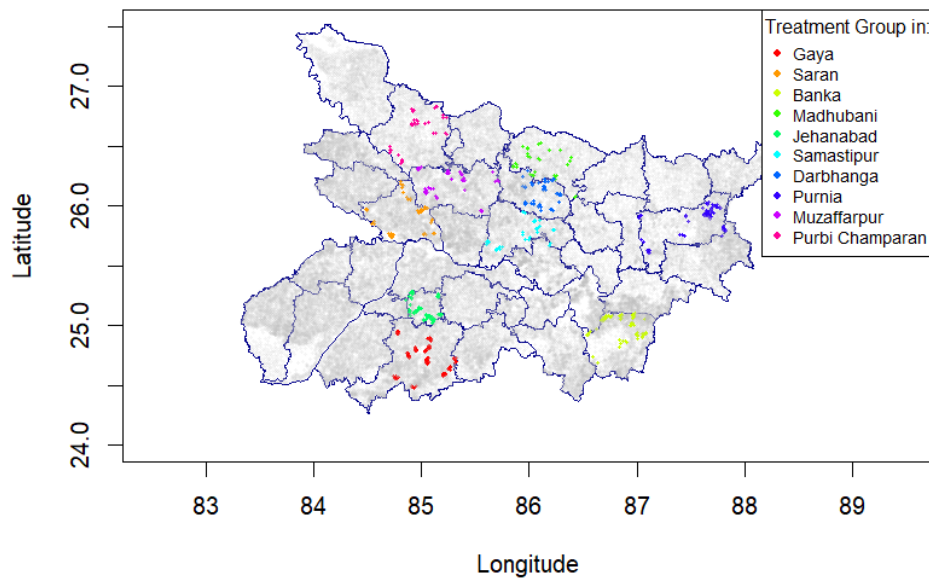


Notes: This figure describes the first and second stage sampling strategy of our study. The first row details the sampled districts along with the total gram panchayats sampled, the second row shows the first stage of randomisation by treated and control GPs within each sampled districts. Randomisation of GPs into treatment and control is done at the district level, with 85% of the GPs being sampled within a 55 KM radius to the district centre (Refer to table A4 in the appendix for GP level sampling strategy). The second stage randomisation is shown in the third row. Within a treated GP, there can be 4-6 wards surveyed, two being spillover wards and two to four wards being treated to peer group discussions (Refer to table A5 in the appendix for ward level sampling strategy).

Figure A2. Maps of Experiment Area and Sample Treated Groups from Each District

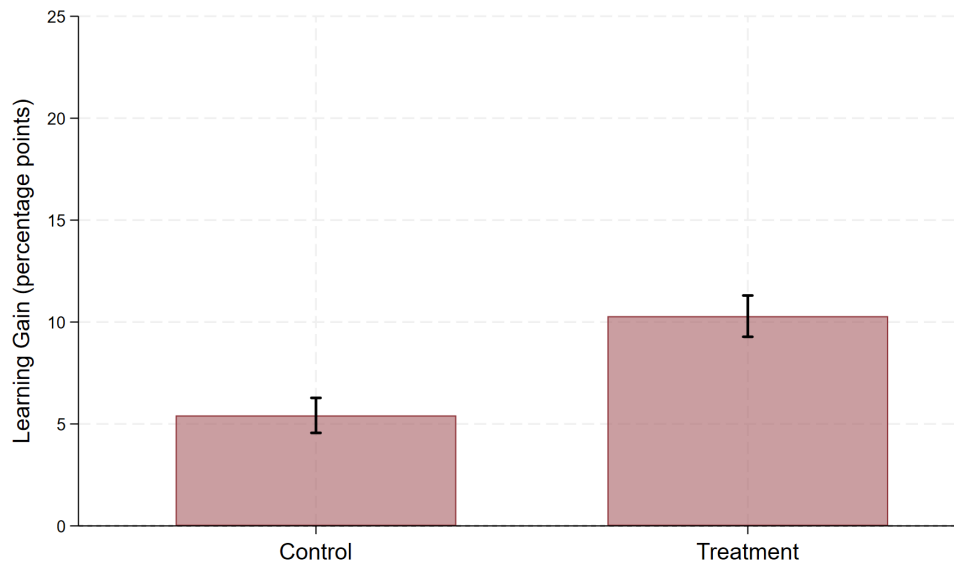


(a) The above figure marks all villages demarcated in the state of Bihar. The villages filled in blue refer to villages belonging to the treatment and control GPs in the experiment. Villages filled in grey show villages outside the study sample.



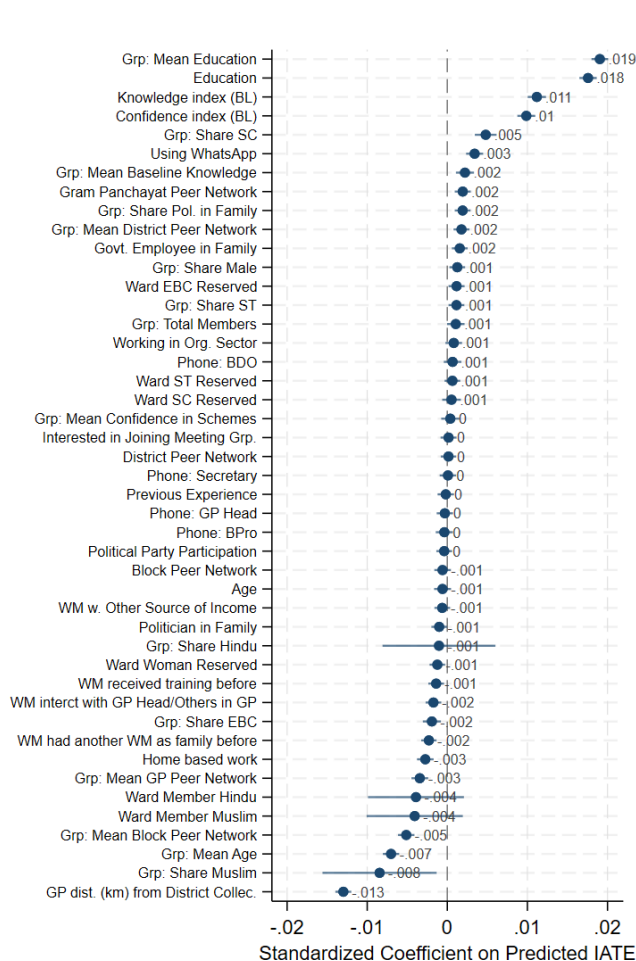
(b) The above figure shows the dispersion of ward members that belong to the same peer group. Each colored category (non-gray) represents the different GPs from which each member(s) of the peer group belongs. Selection of the peer groups for illustration was done randomly for each district.

Figure A3. Change in Mean Knowledge from Baseline to Endline for Control Ward Members

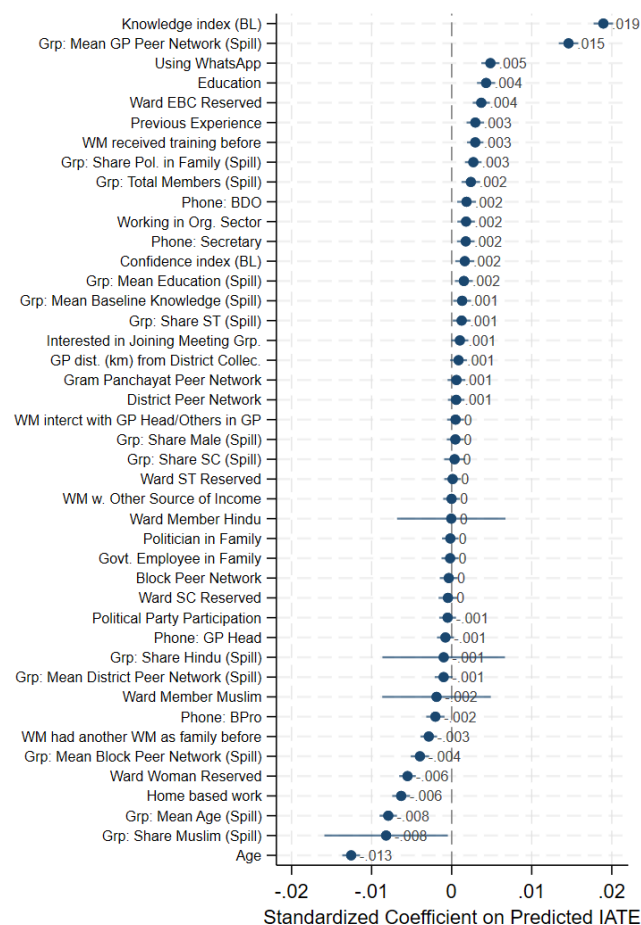


Notes: The above table shows the percentage gain in the number of steps known by ward members on scheme implementation for control and treatment groups. For estimating the count of steps known by each ward member in the above figure, we restrict the total number of questions related to the steps to those that are asked at both baseline and endline. The schemes included are PDS, Pension, Solar Lights, Drains and Lanes, and Housing. 90% confidence intervals are used for each bar plot.

Figure A4. Heterogeneous Direct and Spillover Effects for Combined Knowledge Index



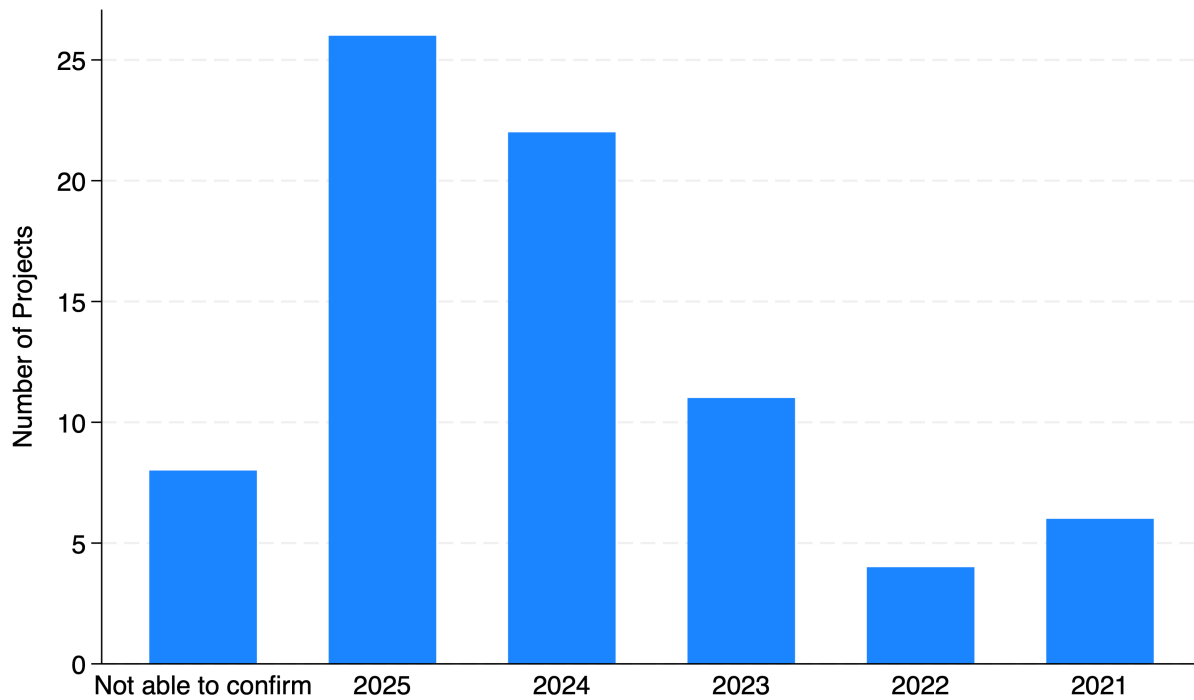
(a) Coefficient Plot of predicted CATE estimates – Group and Individual Characteristics



(b) Coefficient Plot of predicted and conditional spillover effects (using CATE) – Group and Individual Characteristics

Notes: The above figure plots the correlates for different individual and group level characteristics when regressed on a) the predicted conditional average treatment effects and b) the predicted CATE for spillovers. All group level variables are denoted with the prefix “Grp”. The prefix “Phone” denotes variables where the WM has access to the phone number of the politician/bureaucrat whose designation proceeds the prefix. BL denotes baseline. The variable “previous experience” refers to ward members who either have been elected as ward members before or have family members who hold/held political positions. All group and individual variables are standardized for regressions and were reocoded at baseline.

Figure A5. GPDP Audit Survey Data by Year



Notes: The above figure uses data from the GPDP audit survey and enumerates the number of projects verified to have been undertaken in each year. The projects categorised under “Not able to confirm”, refer to those projects in the admin data which were found on site but whose year of initiation could not be confirmed. The above data includes both ongoing and completed projects that were verified through the audit.

E Learning from WhatsApp Groups

As a complement to the meeting-level measures of scheme discussion used in the main text, we exploit the content of WhatsApp group conversations to construct an alternative measure of scheme-specific engagement. The intervention created 208 WhatsApp groups, generating 24,158 non-moderator messages over the study period. We classify messages as scheme-related using a dictionary of 219 keyword aliases (in Hindi, English, and transliterated forms) spanning the nine government schemes discussed in the peer groups. Applying this dictionary with fuzzy matching (85% similarity threshold) and contextual exclusion rules, we identify 3,659 messages (15.1%) with a direct scheme keyword match. Validation against a hand-coded gold standard of 2,664 messages yields an overall precision of 0.85 and recall of 0.88. There is substantial variation across groups in the volume of scheme-related messages: the mean is 17.8 messages per group (direct matches only), but the median is just 9 (SD = 25.0), reflecting a right-skewed distribution. The most frequently discussed schemes are solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA) (mean 6.2 messages per group), provision of tap water (*Nal Jal*) (4.9), and NREGA (2.4).

We estimate heterogeneous treatment effects along two dimensions. We use a $WM \times$ scheme specification with scheme fixed effects (mirroring the main paper's structure). Second, we vary the *functional form* of the heterogeneity measure: a binary indicator for above-median discussion (our baseline, paralleling the binary splits used elsewhere in the paper) and a continuous z-scored measure of discussion intensity (standardized among treatment groups, set to zero for controls). The continuous measure uses the full variation in discussion volume rather than imposing an arbitrary median split.

We begin with the ward member $\times$ scheme specification that parallels the main paper's heterogeneity tables. In the binary specification (Table A40), the above-median scheme discussion indicator is not individually significant for any of the five learning outcomes, including the combined index (0.029, SE = 0.021). However, using the continuous measure at the scheme level (Table A41), a one-standard-deviation increase in scheme-specific discussion is associated with a 0.023 SD increase in best practices knowledge (significant at the 10% level) and a 0.022 SD increase in the combined index (significant at the 10% level).

F Attrition-Adjusted Estimates

The endline survey reached 6,213 ward members, compared to 7,277 at baseline. Table [A29](#) suggests that on most dimensions, those found at endline look no different from those we missed out on. The one dimension where we find some consistent evidence of a difference is caste: among those we find at endline, the proportion of SCs is larger.

Next, we test whether our endline respondents differ by treatment arm. Table [A31](#) confirms that the endline sample remains balanced across treatment, control, and spillover arms on observable baseline characteristics.

The composition of attrition nonetheless differs by arm: relative to baseline, the endline sample contains fewer treated and fewer control ward members, but *more* spillover ward members (see last three rows of Table [A29](#)). Because attrition is non-random with respect to treatment assignment, restricting analysis to endline respondents may yield biased estimates of treatment and spillover effects. We address this concern with two complementary approaches: doubly robust inverse-probability-weighted estimates and [Lee \(2009\)](#) bounds.

Doubly Robust Estimates

We follow the doubly robust (DR) estimator of [Scharfstein et al. \(1999\)](#), adapted for experimental settings with clustered assignment. For each outcome–combined knowledge index (treatment and spillover effects), confidence index, networks index, and relationship with GP head—we proceed in two steps. First, we regress each outcome on baseline covariates using the full baseline sample to obtain predicted values for all observations, including those lost to attrition. Second, we model selection into the endline sample as a function of the same baseline covariates, producing inverse probability weights (IPWs) that reweight endline respondents to approximate the baseline population. The DR estimator augments the IPW-reweighted estimator with a correction term that adjusts for discrepancies between predicted and realized outcomes, scaled by the inverse selection probability. The estimator is consistent if either the outcome model or the selection model is correctly specified—hence the “double robustness.” Standard errors are obtained via 500 cluster bootstrap replications.

Table [A33](#) shows that treatment effects on all five outcomes are stable in sign, magnitude, and significance relative to the primary estimates. Spillover effects on the knowledge index are similarly robust; remaining spillover estimates retain the same sign but are less precisely estimated, consistent with the smaller effective sample in that arm.

Lee Bounds

We complement the DR estimates with the bounding approach of [Lee \(2009\)](#), which imposes no parametric assumptions on the selection process. The procedure equalizes response rates across arms by trimming the “excess” respondents from the higher-response arm—those with the most favorable outcomes for the lower bound, and those with the least favorable outcomes for the upper bound—bracketing the treatment effect under worst-case and best-case selection. We further tighten the bounds by performing the trimming within two strata of the predicted response probability, above and below the median, where the prediction comes from a logit of the response indicator on baseline covariates and district fixed effects. Standard errors come from 200 cluster bootstrap replications at the GP level.

Table [A35](#) reports the bounds and the Imbens-Manski 95% confidence interval for the treatment-effect parameter. In the treatment-versus-control sample, both bounds are positive for all four outcomes, and the Imbens-Manski interval excludes zero for the combined knowledge index, the professional networks index, and the relationship with the GP head. In the spillover-versus-control sample, where differential attrition is more than twice as large (7.3% versus 2.9%), the Imbens-Manski interval for the combined knowledge index includes zero, though the lower and upper bounds are both greater than zero.

G Appendix: Construction of Key Variables

G.1 Knowledge

We measure ward members (WMs) knowledge in five ways:

1. **Formal Knowledge Index:** Peer networks could enhance WMs' understanding of scheme implementation across the spectrum of schemes that affect their constituents. This includes both formal steps and informal (tacit) practices commonly used in the field.⁴¹ We measure the former using a Formal Knowledge Index, which comprises responses to questions about the formal steps required to implement seven major schemes (randomised): solid and liquid waste management (*Lohia Swachhta Bihar Abhiyan*, LSBA), drains and lanes constructions (*Nali Gali*), subsidies for house constructions (*Prdhan Mantri Awas Yojna*, PMAY), solar lights, subsidised food rations (Public Distribution System, PDS), pensions (Old age pensions), and subsidy for toilet constructions (*Swachh Bharat Mission*, SBM). For each scheme, a checklist of steps was compiled using official manuals and interviews with bureaucrats and WMs in both treatment and control groups. The formal steps have the suffix "(F)" in Table F1.⁴²
2. **Tacit Knowledge Index:** Analogous to the Formal Knowledge Index, we construct a Tacit Knowledge Index using the same set of questions (few schemes had only formal steps and no tacit steps, Table F1) but based on responses pertaining to tacit knowledge and informal practices. These informal steps are as important as formal ones for understanding the complete flow of activities, yet they are not documented in any official guidelines. Examples include knowing to who will handover this list of potential works under certain scheme, or to whom this list must be submitted at the block level. Such knowledge is essential for a Ward Member to understand the expected timelines for specific tasks and the procedural workflow involved. The tacit knowledge steps in the table are denoted by the suffix "(T)".

We construct the Formal Knowledge Index and Tacit Knowledge Index as follows: For the Formal Knowledge Index, for each scheme, we calculate the proportion of formal steps correctly identified by a WM, defined as the number of formal steps reported by the WM divided by the maximum number of formal steps reported by

⁴¹Treated WMs could acquire this knowledge through peer group discussions that expose them to best practices and practical know-how from more experienced members.

⁴²For instance, drains and lanes construction requires a ward meeting to identify the site, Gram Sabha approval, an engineer's cost estimate, and milestone-linked disbursements.

any WM for that scheme. We then average these proportions across all schemes to obtain a single score for each WM. Finally, we standardize this score — subtracting the mean and dividing by the standard deviation across all WMs in the control group — to construct the final index. We construct the Tacit Knowledge Index using the same procedure. See Table F1 for the questions included in the construction of the Formal and Tacit Knowledge Indices.

3. **Procedural Knowledge Index:** While the first two indices use a relative scoring method and primarily captures WMs’ breadth of knowledge with respect to how a range of schemes get implemented, we construct another measure — the Procedural Knowledge Index — to capture their knowledge about what is supposed to be done, based strictly on rules. Peer networks could improve WMs’ understanding of formal (de jure) rules that govern scheme implementation — such as eligibility criteria, official documentation requirements, and reporting protocols — specifically as they relate to the schemes where WMs have official responsibilities.

The Procedural Knowledge Index comprises four objectively scored components: two on Solar street Lights (decision on the number of lights and their placement), one on solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA) (who should appoint sanitation workers), and work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA) (who should take attendance of workers at the worksite). WMs were asked factual questions with objectively correct answers about scheme rules. Each component is a binary variable coded 1 if the respondent’s answer is correct and 0 otherwise. These binary components are first standardized (converted into z-scores), and we take the average of these standardized scores for each WM. We then standardize this score with respect to the control mean average and standard deviations to arrive at the final index. See Table F3 for the questions included in the construction of this index.

4. **Best Practices Index:** We measure another facet of knowledge that relates to judgment and strategic problem-solving in the face of real-world implementation issues using the Best Practices Index. Peer learning could help WMs identify practical solutions to common implementation challenges. Through peer group discussions, WMs may exchange strategies, troubleshoot collectively, and become more effective at navigating block-level bureaucracies or resolving delivery failures.

This index draws on scenario-based questions. The WMs’ responses were evaluated based on whether they proposed specific, effective actions. Generic responses (e.g.,

“talk to the GP head”) were not included in the index. See the italicized options that were included in the index presented in Table F4.⁴³

We construct the index in the following way: for each of six schemes (subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), subsidised food rations (Public Distribution System, PDS), Solar street lights, solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), Provision of tap water (*Nal Jal*) and NREGA), we calculate the number of effective recommendations mentioned by the WM. We then standardize this count for each scheme, followed by taking a mean of the Z-scores of individual components. We then standardize this score with respect to the control mean average and standard deviations to arrive at the final index.

5. **Combined Index:** Finally, we include an index of the first four knowledge indices.

Together, these four indices – and the combined index – provide a multidimensional view of WM knowledge by capturing not just factual understanding of rules and procedures, but also practical familiarity with implementation processes and the capacity to devise effective solutions to real-world governance challenges.

G.2 Networks

Peer learning groups could strengthen WMs’ professional networks by exposing them to the networks of other group members. Through repeated group meetings, a WM may learn about and gain access to contacts that peers have cultivated — whether ward members from other blocks, higher-tiered bureaucrats, or political actors. For instance, a more experienced WM might refer a peer to a responsive Block Development Officer (BDO) or connect them with a political leader who can help resolve a local issue. For newly elected representatives, such connections are otherwise difficult to establish independently. We measure these networks along three dimensions.

1. **Outside-GP WM Network:** A WM’s effectiveness often depends on access to peers beyond their own Gram Panchayat who can share experiences, offer advice, and provide information about scheme implementation in other wards. Peer meetings can expand this network both directly — by bringing together ward members from different panchayats and blocks — and indirectly, by enabling WMs to cultivate connections through the peer networks of fellow group members. We measure this using

⁴³For instance, for the first scenario in which a beneficiary in a ward had not received the cash transfer under the toilet construction scheme, we identified effective solutions — in this case, these were filing a collective petition, speaking to a specific bureaucrat named the Swachhta Grihi, or speaking to the assigned data operator for the scheme.

two questions: the number of WMs from outside their GP that respondents report having conversations with regarding difficulties faced at work, and who they generally turn to when they face a work-related difficulty. We standardize this measure - by subtracting the control group mean and dividing by the control group standard deviation.

2. **Block-Level Bureaucrat Network:** Navigating the administrative machinery requires WMs to interact with key block-level officials, particularly the BDO and the Block *Panchayati Raj* Officer (BPRO). These officials oversee scheme approvals, fund disbursements, and administrative clearances that are critical to project implementation at the ward level.⁴⁴ We capture the strength of these relationships using variables measuring the frequency of interactions with the BDO and BPRO. We construct a standardized index from these variables following the same procedure as above.
3. **Political Party Network:** Political connections can serve as an important resource for WMs in securing support for ward-level projects, mobilizing resources, and navigating political processes. We measure this using a variable capturing a WM's links to political parties - specifically, whether the WM or any of their family members were involved with a political party in any capacity. We construct a standardized score from this variable using the same procedure.

Finally, we construct a **Combined Network Index** by averaging the three standardized indices above and add one more variable using the control group mean and standard deviation. This composite measure captures the overall breadth of a WM's professional network across peers, bureaucrats, and political actors. See Table F6 for these network questions.

G.3 Confidence

We construct a Confidence Index based on the number of schemes (out of 19) for which a WM reports feeling confident in implementing. This index captures the extent to which WMs feel equipped to fulfil their governance responsibilities. It is constructed by standardizing the raw count using the control group mean and standard deviation. See Table F7 shows the question used to construct the Confidence Index.

⁴⁴For instance, construction works under house construction (*Pradhan Mantri Awas Yojana*, PMAY) or drains and lanes construction *Nali Gali* require cost estimates and approvals routed through the block office, making a WM's relationship with the BDO and BPRO consequential for timely execution.

G.4 Conflict

Our conflict measures are drawn from an endline question on whether, since Holi 2023, the WM had any conflict, dispute, or argument with a public representative or government employee in the Panchayat, Block, or District in relation to work, and if so, with whom (see Table F8). WMs selected from a list of public representatives and government employees. We construct separate binary indicators for conflict with each type of actor. The main analysis reports indicators for conflict with the GP Head, GP NREGA Assistant (*Rozgar Sevak*), and GP Secretary (*Panchayat Sachiv*).

We measure WM–GP Head relationships using a question asking WMs to rate their relationship with the GP Head on a five-point scale, from very bad to very good (see Table F8). We construct a binary variable equal to 1 for a bad relationship (responses of 1 or 2) and 0 otherwise.

We measure regular Gram Sabha participation using a question on whether WMs had participated in Gram Sabha meetings since Holi 2023, and if so, how many times (see Table F8). We construct an indicator equal to one if a WM reported attending at least four meetings and zero otherwise.

G.5 GPDP Analysis

We use Gram Panchayat development Plans (GPDP) administrative data on planned projects and their estimated costs. Each project record includes a project description, as well as fields identifying the broader theme and sector. We use these fields, together with iterative cleaning and keyword matching of project descriptions, to classify projects to scheme categories. This process yields 18 identified scheme categories: subsidy on house construction (*Pradhan Mantri Awas Yojana*, PMAY), Health insurance (*Ayushman Card*), Education, Water conservation (*Jal Jeevan Hariyali*, JJH), Healthcare, Marriage assistance (*Mukhyamantri Kanya Vivah Yojana*, MKVY), Public grievance redressal (*Lok shikayat*), Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (*Nali-Gali*), Provision of tap water (*Nal-Jal*), Pension, Subsidised food rations (Public Distribution System, PDS), Public service delivery (Right to Public Services, RTPS), Educational financial assistance (Scholarship), Solar Street Lights, subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), and Entrepreneurship support (*Mukhyamantri Udyami Yojana*, MUY).

Projects that cannot be assigned reliably to a specific scheme are retained in a separate “Uncategorized” category rather than being dropped. These are projects for which the

available description, theme, and sector information do not permit a credible scheme assignment. We then aggregate project-level information to construct GP-scheme measures of the number of planned projects and total planned expenditure. The relevant table notes indicate whether specifications include the Uncategorized category.

G.6 Ward Member Campaign Priorities

At baseline, WMs were asked what issues they had campaigned on to win the election. WMs selected from a list of schemes and could select more than one issue. We construct a separate binary indicator for each scheme, equal to one if the WM reported campaigning on that issue.

For the analysis, we retain eight campaign categories that are also used elsewhere in the study: subsidy on house construction (*Pradhan Mantri Awas Yojana*, PMAY), NREGA, drains and lanes construction (*Nali Gali*), provision of tap water (*Nal Jal*), Pension, subsidised food rations (Public Distribution System, PDS), Solar street Lights, and subsidy on toilet construction (*Swachh Bharat Abhiyan*, SBM). The remaining baseline campaign categories are not used because they do not appear in the endline survey, citizen survey, or peer-group meeting data. For GP-scheme analyses, we calculate the share of sampled WMs in each GP who reported campaigning on a given scheme.

G.7 Citizen Preferences

In the endline citizen survey, respondents were asked: “What are the two schemes or issues where the Ward Member (WM) or GP Head should increase spending?” Respondents selected from a list of 18 schemes and could name at most two. The schemes were: subsidy on house construction (*Pradhan Mantri Awas Yojana*, PMAY), Health insurance (*Ayushman Card*), Education, Water conservation (*Jal Jeevan Hariyali*, JJH), Healthcare, Marriage assistance (*Mukhyamantri Kanya Vivah Yojana*, MKVY), Public grievance redressal (*Lok shikayat*), Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), Work provided under employment guarantee (National Rural Employment Guarantee Act, NREGA), Drains and lanes construction (*Nali-Gali*), Provision of tap water (*Nal-Jal*), Pension, Subsidised food rations (Public Distribution System, PDS), Public service delivery (Right to Public Services, RTPS), Educational financial assistance (Scholarship), Solar Street Lights, subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), and Entrepreneurship support (*Mukhyamantri Udyami Yojana*, MUY). We convert these responses into 18 binary indicators, one for each scheme, equal to one if the respondent selected that scheme. For analyses at the GP-scheme level, we calculate the share of sampled citizens in each GP

who selected a given scheme.

G.8 Citizen Assessments

We assess treatment effects on citizens' experiences with two categories of schemes: public goods provision of drains and lanes construction (*Nali-Gali*), provision of tap water (*Nal-Jal*), Solar street Lights, and solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA) and welfare programs (NREGA, subsidised food rations (Public Distribution System, PDS), pensions, subsidy on Toilet construction (*Swachh Bharat Abhiyan*, SBM), and subsidy on House construction (*Pradhan Mantri Awas Yojana*, PMAY). For each category, we construct scheme-specific standardized indices and a combined index aggregating across all schemes within that category (following [Kling et al. \(2007\)](#)). All outcomes are standardized using the control group mean and standard deviation.

Effects on Citizen Reports of Public Goods and Welfare Programs. For public goods, we ask citizens whether specific infrastructure or services have been delivered since *Holi* 2023 in their ward:

- **Drainage and lanes construction (*Nali-Gali*):** whether any construction of lanes or drains has taken place in the ward under the Nali-Gali scheme, and if so, in which years.
- **provision of tap water (*Nal-Jal*):** whether the household has received a water connection through the Nal Jal scheme, and if so, when.
- **Solar street Lights:** whether solar streetlights have been installed in the ward, and if so, in which years.
- **solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan*, (LSBA):** whether a sanitation worker (*Swacchta Karmi*) has been visiting the household to collect waste, and if so, since when.

For welfare programs, we ask citizens whether they or their household members have accessed or applied for key schemes since *Holi* 2023:

- **NREGA:** whether anyone in the household has received a job card or applied for one since *Holi* 2023.
- **Subsidised food rations, Public Distribution System (PDS):** whether the household applied for or made any changes to a ration card since *Holi* 2023.

- **Pension:** whether anyone in the household received or applied for an old-age pension since Holi 2023.
- **Subsidy on toilet construction (*Swachh Bharat Abhiyan,SBM*):** whether a toilet has been constructed in the household through the government scheme, or whether the household has applied for it, since Holi 2023.
- **subsidy on house construction (*Pradhan Mantri Awas Yojana, PMAY*):** whether the household received or requested assistance from the Awas Yojana to build a house since Holi 2023.

We report treatment effects on public goods outcomes, and on welfare program outcomes. We also construct a combined index for each type of outcome aggregating across all schemes within that category. Controls include baseline knowledge and networks (at the district, block, and GP level) of corresponding ward members and citizens' age, gender, caste, religion, education, and primary source of income. Standard errors are clustered at the UGP level.

G.9 Treatment Effects on Self-Dealing and Citizen Reports of Bribe.

We examine two dimensions of potential malfeasance by ward members. Firstly we examine self-dealing using administrative data on NREGA works. We measure whether treated ward members disproportionately directed NREGA benefits toward their own households. Specifically, we examine the share of NREGA days worked by ward members' households within their GP, whether the ward member's household worked at all, and the total day count of NREGA work for ward member households, for both the 2023–2025 and 2024–2025 periods.

Then we examine citizen reports of bribes taken by ward members across various welfare schemes. For each scheme, we ask citizens whether they had to pay anything in cash or kind to anyone to receive the benefit, and if so, to whom:

- **NREGA:** combines responses across three stages — whether the household paid bribes to receive the job card, to receive work, or to receive payment.
- **Subsidised food rations, Public Distribution System PDS):** whether the household paid anything to receive the ration card.
- **Subsidy on toilet construction (*Swachh Bharat Abhiyan,SBM*):** whether the household paid anything to receive the toilet scheme benefit.

- *Pension*: whether the household paid anything to receive the pension.
- **subsidy on house construction** (*Pradhan Mantri Awas Yojana, PMAY*): whether the household paid anything to receive the benefit of the Awas Yojana.

We construct a combined bribe index aggregating across all schemes. GP controls include total population, number of villages, total area, distance from district HQ, and distance from nearest town. Ward controls include baseline knowledge and networks of the ward members, gender, age, caste, and years of education. Standard errors are clustered at the UGP level.

G.10 Rivalrous and Non-Rivalrous Schemes

We classify the seven schemes into two categories based on whether the allocation of benefits within a GP is rivalrous across wards. A scheme is *rivalrous* if resources or physical works directed to one ward necessarily reduce what is available to another ward within the same GP in a given planning cycle.

Three schemes fall into the rivalrous category: Draines and lanes construction (*Nali-Gali*), Provision of tap water *Nal Jal*, and NREGA. In each of these cases, funds flow directly from the GP. For draines and lanes construction and provision of tap water, while in the pre-2021 era each ward was allocated funds ([Sharan, 2021](#)), all funding was routed through the GP post-May 2023. Hence, ward members could bargain for funds only via the GPDP (GP Development Plans), which involved negotiations with the GP head, with roughly fixed resources earmarked in every GP, implying direct competition with other wards. For NREGA, the law mandates that work is provided to any worker on demand, but NREGA work is largely supply-driven in Bihar ([Banerjee et al., 2020](#)). Once again, projects and funds are allocated by the GP head – and typically, there is a fixed set of resources each GP can allocate for projects. The GP head submits a shelf of works to upper authorities to authorize – ward members’ principal way of allocating resources for NREGA in their ward is to try and get projects in their ward to be on the shelf that is submitted. Once again, there is typically a cap on the number of projects that a GP head submits – hence wards compete against other to get works allocated.

By contrast, Solid and liquid waste management (*Lohiya Swachh Bharat Abhiyan, LSBA*) and Solar street Lights are classified as *non-rivalrous*, since both the allocation rules and phasing decisions are determined by higher authorities – not the GP head – and the rules stipulate that separate funding exist for each ward. For solar lights, for instance, every ward is allocated 10 lights in a fixed order of priority (based on the ward’s number). Thus, there are funds for every ward to get access to lights. Similarly for LSBA, as per the rules,

every ward is allocated funds for dustbins, a trash collector (*Swachta Karmi*) and soak pits. Welfare schemes like subsidy on house construction (*Pradhan Mantri Awas Yojana*, PMAY), subsidy on toilet construction (*Swachh Bharat Abhiyan*, SBM), subsidised food rations (Public Distribution System, PDS), and pensions are similarly non-rivalrous, but for a distinct reason: these are individual- or household-level entitlement schemes, where eligibility is determined by fixed criteria (income, asset ownership, age) rather than by GP- or ward-level budget ceilings. A ward member sharing knowledge of the application process for one household's pension or ration card does not reduce another household's – even one in a different ward – chances of receiving the same benefit, since beneficiaries are not competing against each other within a finite, locally-allocated quota.

Table F1. Formal (F) and Tacit (T) Knowledge Index Questions (Part 1)

Question	Steps
If you want to get work done in your ward under the lanes and drain construction scheme <i>Nali gali</i> , what steps need to be taken?	1. A ward meeting will be held to select the site for construction. (F) 2. The plan will be passed in the Gram Sabha. (F) 3. The Mukhiya will submit this list for the year at the block-level Panchayat office. (T) 4. After the scheme is uploaded to the portal, priority will be given to Dalit and Maha Dalit areas. (T) 5. The Junior Engineer (JE) will prepare the estimate. (T) 6. The work will be assigned to a contractor or agency selected by the block. (F) 7. The JE will prepare the Measurement Book (MB) after 25% of the work is completed. (F) 8. Geo-tagging will be done. (F) 9. An initial payment will be made to the contractor through the Ward Implementation and Management Committee (WIMC). (F) 10. After inspection, the remaining amount will be released. (F) 99. Don't know / don't remember. 100. Others
Under the solar light scheme in your ward, what needs to be done if you want to install a solar light?	1. Each ward will receive 10 solar lights. (F) 2. The scheme is implemented in phases—first four wards, then the next set. (F) 3. The Ward Member (WM) will prepare a list and submit it to the Mukhiya. (F) 4. A Ward Sabha will be held to finalize the installation sites. (F) 5. The list is submitted to the Panchayat. (T) 6. The Mukhiya and Panchayat Secretary will approve the installations upon state allotment. (T) 7. The Bihar Renewable Energy Development Agency (BREDA) company will install the lights under WM supervision. (T) 99. Don't know / don't remember. 100. Others
If you need to implement LSBA in your ward, what steps would you need to take?	1. The Gram Panchayat will be selected by the block office for LSBA implementation. (T) 2. The Mukhiya will call a meeting with WM and identify a site for the Waste Processing Unit (WPU). (T) 3. Construction of the WPU will begin. (F) 4. WMs will prepare a list of interested households. (F) 5. Two dustbins will be distributed to each household. (F) 6. Ward Sabhas will be conducted to select Swachhta Karmis. (F) 7. The Mukhiya will appoint a Swachhta Supervisor. (F) 8. Garbage vehicles/cycles will be distributed to each ward. (F) 9. The Ward Sabha will fix garbage collection timing and set a monthly fee. (T) 99. Don't know / don't remember. 100. Others
If someone in your ward wants to benefit from the Pradhan Mantri Awas Scheme, what steps need to be taken?	1. The WM will check if the online portal is open. (T) 2. A list of eligible households with ID, caste, and address proof will be prepared. (F) 3. The list will be updated based on SC and SECC data. (F) 4. The Awas Sahayak and WM will verify the documents. (F) 5. The list will be submitted through the Mukhiya to the block office. (T) 6. Upon approval, the beneficiary's name will be added to the portal and the first installment will be credited. (F) 7. Construction will begin, and the second installment will be released after verification. (F) 99. Don't know / don't remember. 100. Others
If someone in your ward wants to benefit from the Toilet Scheme, what steps need to be taken?	1. The WM will prepare a list of eligible households with ID, caste, and address proof. (F) 2. The Swachhta Grihi and WM will verify eligibility and check for existing toilets. (F) 3. The list will be submitted to the block office through the Mukhiya. (F) 4. Once approved, the beneficiary is instructed to construct the toilet. (F) 5. Geo-tagging is done by the Swachhta Grihi with the help of the WM. (F) 6. Upon approval of geo-tagging, 12,000 will be transferred to the beneficiary's account. (F) 99. Don't know / don't remember. 100. Others

Table F2. Formal (F) and Tacit (T) Knowledge Index Questions (Part 2)

Question	Steps
If someone in your ward needs to get a ration card, what steps need to be taken?	1. Carry original and photocopies of Aadhar card, caste certificate, and bonafide certificate. (F) 2. Bring original and photocopies of the bank passbook. (F) 3. Have a family group photo (at least one). (F) 4. Apply at the Right to Public Services (RTPS) counter in the block office, Common Service Centre (CSC), or online on the EPDS website. (F) 5. Submit documents at the Subdivision Office (SDO) for approval. (F) 99. Don't know / don't remember. 100. Others
If someone in your ward wants to benefit from the Vriddha Pension Scheme, what steps need to be taken?	1. The applicant should be 60 years or older. (F) 2. Carry original and photocopies of the Aadhar card. (F) 3. Carry original and photocopies of the Voter ID. (F) 4. Carry original and photocopies of the bank passbook. (F) 5. Ensure the name matches across all documents. (F) 6. The date of birth should match in Aadhar and Voter ID. (F) 7. Apply at the RTPS counter in the block office, CSC, or online through the state portal. (F) 8. Complete e-KYC. (F) 99. Don't know / don't remember. 100. Others

Table F3. Procedural Knowledge Index Questions

Question	Response Options
According to government rules, who is responsible for selecting the location of the solar lights within the ward under the Solar Light Scheme?	1. Ward Member/Ward Sabha/WIMC 2. Mukhiya 3. Panchayat Secretary 4. Ward Secretary 5. Block level officials 6. BREDA Company 7. Contractor 99. Don't know 100. Others
According to the government rules, who should appoint sanitation workers in the ward under Lohia Swachh Bihar Abhiyan Scheme?	1. Ward Member/Ward Sabha/WIMC 2. Mukhiya 3. Panchayat Secretary 4. Ward Secretary 5. Block level officials 99. Don't know 100. Others
According to government rules, how many solar lights should be installed in one ward under the solar light scheme?	(In rules - 10 per ward)
As per government rules, under MGNREGA scheme, who should take attendance of MGNREGA workers?	0. No work is getting done here 1. Panchayat Rozgar Sevak (PRS) 2. MGNREGA Mate 3. Jeevika Didi 4. Any female worker among those who is not a mate 5. Any worker who is not a mate 6. Panchayat Secretary 7. Mukhiya 8. Ward Member 99. Don't know 98. Don't want to say 100. Other

Table F4. Best Practices Index Questions (Part 1)

Scenario	Suggested Approaches	
If ward members from another panchayat come to you with the issue that a beneficiary in their ward has not yet received money under the Toilet (Shauchalay) scheme, how would you advise them to resolve this issue? What methods or approaches would you suggest to the ward member to solve this problem?	0. Do nothing 1. Speak to other WM for information/ advice 2. Speak to Mukhiya 3. Speak to Block Development Office/Officer (BDO)/Block Panchayati Raj Officer (BPRO) 4. Speak to District Development Commissioner (DDC)/ District Panchayati Raj Officer (DPRO) 5. Speak to District Magistrate DM 6. Speak to Panchayat Secretary (PS) 7. Protest with WMs 8. Protest with citizens 9. File online/ offline Complaint through Lok Shikayat Nivaran	10. Right to Information (RTI) 11. <i>File a collective petition</i> 12. <i>Speak to Swachhta Grihi</i> 13. <i>Speak to Toilet data operator</i> 14. Speak to Block Coordinator (BC) 15. Speak to Vikas Mitra (VM)(Appointed from the marginalized and disadvantaged community by the state government at the panchayat level to facilitate any government schemes) 16. Speak to any other officer at the block not mentioned in the list 99. Don't know 100. Others
If ward members from another panchayat approach you because some people in their ward are not receiving their ration, what methods or approaches would you suggest to solve this problem?	0. Do nothing 1. Speak to other WM for information/ advice 2. Speak to Mukhiya 3. Speak to BDO/BPRO 4. Speak to DDC/DPRO 5. Speak to DM 6. Speak to PS 7. Protest with WMs 8. Protest with citizens 9. File online/ offline Complaint through Lok Shikayat Nivaran 10. RTI 11. File a collective petition	12. <i>Speak to Public Distribution System (PDS) Contractor</i> 13. <i>Speak to Marketing Officer (MO)</i> 14. <i>RTPS operator</i> 15. Speak to BC 16. Speak to VM 17. <i>Speak to any other officer at the block not mentioned in the list</i> 18. Speak to the SDO/other officer at Sub-Division Office 99. Don't know 100. Others
If a few solar lights in the wards of fellow members from another Panchayat have been out of order for a few days, and those ward members approach you with this issue, what methods or approaches would you suggest to solve this problem?	0. Do nothing 1. Speak to other WMs for information/ advice 2. Speak to Mukhiya 3. Speak to BDO/BPRO 4. Speak to DDC/DPRO 5. Speak to DM 6. Speak to PS 7. Protest with WMs 8. <i>Protest with citizens</i> 9. File online/ offline Complaint through Lok Shikayat Nivaran 10. RTI 11. <i>File a collective petition</i>	12. <i>Speak to a BREDA Company person</i> 13. Speak to a Contractor 14. Ask citizen to contribute through collective money 15. Speak to BC 16. Speak to VM 17. Speak to any other officer at the block not mentioned in the list 18. Speak to SDO/other officer at Sub-Division Office 99. Don't know 100. Others
If a fellow ward member from another panchayat approaches you because sanitation workers in their ward haven't received their salary for several months, how would you advise them to resolve this issue?	0. Do nothing 1. Speak to other WMs for information/ advice 2. Speak to Mukhiya 3. Speak to BDO/BPRO 4. Speak to Circle Officer (CO) 5. Speak to MO 6. Speak to DDC/DPRO 7. Speak to DM 8. Speak to PS 9. Protest with WMs 10. Protest with citizens 20. Protest with Sanitation Workers/Supervisor 11. File online/ offline Complaints - Lok Shikayat Nivaran	12. RTI 13. <i>File a collective petition</i> 14. <i>Speak to Sanitation Supervisor</i> 15. Use own Money/Collect money from citizens 16. Speak to BC 17. Speak to VM 18. Speak to any other officer at the block not mentioned in the list 19. Speak to SDO/other officer at Sub-Division Office 99. Don't know 100. Others

Table F5. Best Practices Index Questions (Part 2)

Scenario	Suggested Approaches	
If a motor supplying water under the Nal-Jal scheme in the area of ward members from other panchayats stops working, and they come to you with this issue, what steps or methods would you suggest to solve the problem?	0. Do nothing 1. Speak to other WMs for information/ advice 2. Speak to Mukhiya 3. Speak to BDO/BPRO 4. Speak to DDC/DPRO 5. Speak to DM 6. <i>Speak to PS</i> 7. <i>Speak to JE of Public Health Engineering Department (PHED)</i> 8. <i>Speak to PHED Contractor</i> 9. Speak to any officer in the PHED 21. Contact PHED toll free number 10. Protest with WMs 11. Protest with citizens	12. File online/ offline Complaint through Lok Shikayat Nivaran 13. RTI 14. File a collective petition 15. Use own Money/Collect money from citizens 20. Use Money from the WIMC fund 16. Speak to BC 17. Speak to VM 18. Speak to any other officer at the block not mentioned in the list 19. Speak to SDO/other officer at Sub-Division Office 99. Don't know 100. Others
If fellow ward members from another panchayat are facing difficulties in getting MGNREGA job cards made for people in their ward, and these ward members come to you with this problem, through which means/methods would you advise them to resolve this issue?	0. Do nothing 1. Speak to other WMs for information/ advice 2. Speak to Mukhiya 3. Speak to BDO/BPRO 4. Speak to DDC/DPRO 5. Speak to DM 6. Speak to PS 7. Protest with WMs 8. Protest with citizens 9. File online/ offline Complaint through Lok Shikayat Nivaran 10. RTI 11. <i>File a collective petition</i> 12. Speak to Panchayat Rozgaar Sevak (PRS)	13. <i>Speak to local groups/organisation (Sangathan)</i> 14. <i>Speak to MGNREGA data operator</i> 15. <i>Speak to MGNREGA Block Program officer (BPO)</i> 16. Speak to District Program officer (DPO) 17. Speak to BC 18. Speak to VM 19. Speak to any other officer at the block not mentioned in the list 20. Speak to SDO/other officer at Sub-Division Office 99. Don't know 100. Others

Table F6. Network Index Questions

Question	Response Options
Panel A: Outside-GP WM Network	
Do you have work-related discussions with other ward members outside your GP?	1. Yes 0. No
Outside your GP, how many ward members do you talk to about work?	Integer
Tell us about the ward members outside your GP with whom you have work-related discussions. Start with the one you talk to the most.	For each WM mentioned: 1. District 2. Block 3. Gram Panchayat 4. Name of the Ward Member
Related to work, who do you generally talk to when you face any difficulty?	Other ward members from different GP
Panel B: Block-Level Bureaucrat Network	
Have you ever spoken to the BDO? If yes, when was the last time you spoke to the BDO (either on the phone or in a meeting)?	0. Never 1. From last week till today 2. More than 1 week, but less than 1 month 3. More than 1 month, but less than 3 months 4. More than 3 months, but less than 6 months 5. More than 6 months 98. Don't want to say 99. Don't know / don't remember 100. Others
Panel C: Political Party Network	
Are you or any members of your family involved with a political party? For example, you could be a member, or you could have campaigned for a party, etc.	1. Yes 0. No

Table F7. Ward Members' Confidence in Scheme Knowledge

Scenario	Response Options
Name the schemes for which you feel confident to answer any questions.	97. Did not get any scheme 0. No scheme 1. Nal Jal 2. Nali Gali 3. MGNREGA 4. Old-age Pension 5. Toilet 6. Ration card 8. E-shram card 9. Pradhan Mantri Awas 10. Solar Light 11. Lohia Swachh Bihar Abhiyan - Solid and Liquid Waste Management (LSBA-SLWM) 12. Jal Jeevan Hariyali Abhiyan 13. StudeNet Scholarships 14. Certificates (income, caste, birth/death, residence) 15. Education/School 16. Kanya Vivah Yojana Bihar 17. Aadhaar Card 18. Bihar Lok Shikayat Nivaran 19. Ayushman card 98. Don't want to say 99. Don't know / don't remember 100. Others

Table F8. WM's Conflict

Question	Response Options
Since Holi 2023 last year until now, have you had any conflict/dispute or argument with any public representative or government employee in the Panchayat/Block-/District in relation to work?	1. Yes 0. No
If yes, who were they?	1. Another WM 2. Mukhiya 3. Panchayat Secretary 4. Rozgar Sevak/ PRS 5. Anganwadi Sevika 6. Aasha 7. School teacher 8. Jeevika Didi 9. BDO 10. BPRO 11. Anyone else in Block 12. Anyone else in District 98. Don't want to say 99. Don't know/ don't remember 100. Other
How is your relationship with the Mukhiya? Good or bad? To what extent?	1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good 0. Have never spoken 99. Don't know 98. Don't want to say 100. Other
Since Holi 2023 till now, have you ever participated in Gram Sabha meetings? If yes, how many times have you participated in a Gram Sabha meeting?	Count

Table F9. Campaign Issues Mentioned by Ward Members

Question	Response Options
What were the issues you campaigned on to win the election?	1. Nali-Gali, Sokhta 2. Nal Jal 3. Saat Nischay 4. Ration Card 5. Pension (Old-age Pension, Chief Minister Pension) 6. Shauchalay (Toilet) 7. Indira Awas 8. E-Shram Card / Job Card 9. Corruption 10. MGNREGA 11. Ujjwala 12. Solar Light 100. Others

Table F10. Ward Members' Priorities for Increased Spending

Question	Response Options
What are the two schemes or issues where the Ward Member/Mukhiya should increase spending?	1. Nal Jal 2. Nali Gali 3. MGNREGA 4. Pension (Old-age Pension, Chief Minister Pension) 5. Shauchalay (Toilet) 6. Ration Card 7. Pradhan Mantri Awas 8. Solar Light 9. Lohiya Swachh Bihar Abhiyan – Solid and Liquid Waste Management (LSBA-SLWM) 10. Jal Jeevan Hariyali Abhiyan 11. Scholarships 12. RTPS Certificates (Income, Caste, Birth/Death, Residence) 13. Education/School 14. Kanya Vivah Yojana Bihar 15. Bihar Lok Shikayat 16. Ayushman Card 17. Vishvakarma Yojana / Udyami Yojana / Kaushal Vikas Yojana 18. Any other agriculture-related scheme 19. Healthcare 98. Don't want to say 99. Don't know / Don't remember 100. Others

Table F11. Citizen Survey: Public Goods and Welfare Programmes

Question	Response Options
Public Goods	
Has there ever been any construction of lanes or drains in your ward under the Nali-Gali scheme? If yes, when?	0. No 1. Between 2021 and Holi 2023 2. Before 2021 3. Between Holi 2023 and Diwali 2023 4. Between Diwali 2023 and Holi 2024 5. After Holi 2024 98. Prefer not to say 99. Don't know
Has your household ever received a water connection through the Nal Jal scheme? If yes, when?	0. No 1. Between 2021 and Holi 2023 2. Before 2021 3. Between Holi 2023 and Diwali 2023 4. Between Diwali 2023 and Holi 2024 5. After Holi 2024 98. Prefer not to say 99. Don't know
Have solar street lights ever been installed in your ward? If yes, when were they installed?	0. No 1. Before 2021 2. Between 2021 and Holi 2023 3. Between Holi 2023 and Diwali 2023 4. Between Diwali 2023 and Holi 2024 5. After Holi 2024 98. Prefer not to say 99. Don't know
Has a sanitation worker ever come to your household to collect waste? If yes, since when?	0. No 1. Coming before Holi 2023 2. Coming since Holi 2023 3. Coming since Diwali 2023 4. After Holi 2024 5. Coming before Holi 2023 but no longer 6. Between Holi 2023 and Diwali 2023 7. Between Diwali 2023 and Holi 2024 98. Prefer not to say 99. Don't know / Don't remember
Welfare Schemes	
Has anyone in your family received a job card or applied for one since Holi 2023?	0. No 1. Yes 98. Prefer not to say 99. Don't know / Don't remember
Since Holi 2023, has your household applied for a new ration card or requested any changes to an existing ration card?	0. No 1. Applied for a new ration card but did not receive it 2. Modified an existing ration card 3. Received a new ration card 98. Prefer not to say 99. Don't know
Since Holi 2023, has anyone in your household received or applied for an old-age pension?	0. No 1. Yes 98. Prefer not to say 99. Don't know / Don't remember
Since Holi 2023, has a toilet been constructed for your household under the government sanitation scheme, or have you applied for one?	0. No 1. Money received 2. Applied 98. Prefer not to say 99. Don't know / Don't remember
Since Holi 2023, has your household received assistance or applied for assistance under Pradhan Mantri Awas Yojana to build a house?	0. No 1. Money received 2. Applied 98. Prefer not to say 99. Don't know / Don't remember

Table F12. Bribery for Scheme Access

Question	Response Options
1. Did you have to pay anything in cash or kind to anyone to receive the job card? If yes, who?	0. No
2. Did you have to pay anything in cash or kind to anyone to receive the ration card? If yes, who?	1. Ward member
3. Did you have to pay anything in cash or kind to anyone to get the toilet scheme? If yes, who?	2. Ward sachiv
4. Did you have to pay anything in cash or kind to anyone to receive the pension? If yes, who?	3. Mukhiya
5. Did you have to pay anything in cash or kind to anyone to receive the benefit of the awas yojana? If yes, who?	4. Panchayat Sachiv
	5. Vikas Mitr
	6. Awas Sahayak
	7. Swachhta Grihi
	8. Rozgar Sevak / PRS
	9. JE
	10. Shiksha mitar
	11. Accountant
	12. Contractor/Dealer
	13. Block Coordinator
	14. Peon
	15. BDO
	16. RTPS/ Data Operator/ Sahayak Karyapalak
	17. Parmukh / Up-Pramukh
	18. BPRO
	19. Amin
	20. Kishan Salahkar
	21. Marketing Officer
	22. Circle Officer
	23. MNREGA PO
	98. Don't want to say
	99. Don't know/ don't remember
	100. Others