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

Apurva Bamezai[†] Siddharth George[‡] Siddharth Hari[§]
M.R. Sharan[¶] Munish Sharma [‖]

Friday 27th March, 2026

Abstract

Policies that expand political representation often bring new leaders into office with limited experience of governing. We examine whether peer networks among local politicians facilitate knowledge transfer and improve governance quality. We conduct a large-scale field experiment involving over 7,500 village council members representing 27 million citizens in Bihar, India, randomly assigning some politicians to cross-village peer groups that meet regularly to discuss governance challenges. The intervention expands politicians' professional and political networks and increases their knowledge of procedures, informal practices, and scheme-specific best practices. These gains reflect learning: they are concentrated in groups that exchange more information. Spillovers are large and are higher when treated peers are part of groups with more learning and share social identity. Using administrative data, we show that treated councils plan more projects and allocate greater spending. Moreover, these increases align with citizen priorities and campaign commitments. Together, the results show that peer networks can strengthen political capacity and improve the alignment of public spending with local needs.

Keywords: developing countries, politicians, governance, public service, peer networks

JEL Classification codes: H4, H7, D73, D78, D83, D85

*We are very grateful to Ankita Baidya, Antisha Nigam, Swathi CS, Sawal Choudhary, Ashish Thakur, Shreya Ray, Ria Dutta, Shivani Pandey, Vijay Prakash, and Chanchal Kumar Singh for excellent research support. We also thank Jing Cai, Ritam Chaurey, Frederico Finan, Xavier Gine, Rachel Glennerster, Eeshani Kandpal, Asim Khwaja, Michael Kremer, Martin Mattson, Karthik Muralidharan, Gautam Rao, and Shaoda Wang for helpful feedback. We thank seminar participants at the American University, Centre for Global Development, NUS Singapore, the Singapore Political Economy Workshop, NEUDC (Tufts University), IIM Bangalore and ISI Delhi for comments. We thank anonymous reviewers at the Weiss Fund and JPAL Governance Initiative. Funding from the Weiss Fund, JPAL Governance Initiative and the International Growth Center is gratefully acknowledged. The opinions expressed in the paper are those of the authors and do not necessarily reflect the views of the World Bank Group or its Board of Executive Directors.

[†]University of Notre Dame. abamezai@nd.edu
[‡]National University of Singapore. segeorge@nus.edu.sg
[§]The World Bank. shari@worldbank.org
[¶]University of Maryland. sharan@umd.edu
[‖]GRAMA.munish.94sharma@gmail.com

1 Introduction

Over the past century, the share of countries selecting their leaders through elections has risen from 28% to 84%. In such systems, elected officials must interpret citizen preferences and work within government – alongside bureaucrats and other politicians – to shape policy in line with their constituents' needs. Doing so requires learning how government actually functions. This involves acquiring a formal understanding of the structure of state institutions, the rules governing their operation, and the procedures required to initiate and implement policy. It also entails mastering the tacit norms that shape day-to-day practice: recognising where *de jure* rules diverge from *de facto* realities and identifying the actors whose cooperation is necessary for getting things done.

However, unlike bureaucrats – who typically enjoy stable tenure – politicians face high turnover owing to electoral cycles. As a result, many elected officials enter office with limited prior experience in governing. A substantial share of their time is therefore spent learning on the job, and some learn far more effectively than others, with direct implications for the quality of governance. This challenge has become even more salient as many countries have decentralised authority to increasingly local tiers and instituted affirmative action policies in favour of historically marginalised groups, bringing into office a new cadre of novice politicians (Chattopadhyay and Duflo, 2004). Ensuring that elected representatives learn how to govern has thus become a central concern for modern political systems.

In this paper, we examine whether peer networks can facilitate such learning. Prior research demonstrates that peer interactions shape knowledge acquisition and decision-making in many development contexts. 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). Peer effects also operate in education (Duflo et al., 2011) and the workplace (Sandvik et al., 2020). These findings suggest that peers can serve as an important conduit for both formal information and tacit knowledge. Peer politicians may therefore constitute a natural source of both: formal rules (e.g., guidelines on fund management and programme implementation) and tacit knowledge (e.g., navigating the local bureaucracy).[1] Yet we

[1]Many 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

have little causal evidence on whether peer networks help politicians learn to govern and whether such learning improves governance outcomes.

We evaluate these questions through a large-scale field experiment in Bihar, India. Bihar is India's poorest state and has historically exhibited weak state capacity. We partner with the Government of Bihar's Rural Development Department (RDD) to convene peer groups for extremely local elected representatives known as ward members (WMs). WMs sit within the Gram Panchayat (GP)[2] – the village council – which comprises roughly 13–14 WMs and a directly elected GP head. WMs form the lowest – and most numerous – rung of elected representatives in India: there are over 100,000 in Bihar alone and more than one million nationally.

Across 2,213 GPs, we randomly assigned 968 to treatment and 1245 to control. In treated GPs, 2–4 randomly selected WMs were invited to participate in peer meetings with WMs from other GPs in the same district. Each peer group comprised 10–12 WMs. The experiment therefore enrolled three types of WMs: invited WMs ("treated," 2,424), non-invited WMs from the same GP ("spillover," 1,835), and WMs in control GPs (3,460), yielding a total sample of 7,719 WMs across ten districts.[3] Between January 2024 and July 2025, treated WMs interacted through two in-person meetings, quarterly conference calls, and WhatsApp groups.

There is substantial *ex ante* reason to expect peer-learning effects in this setting. Approximately 70% of WMs are first-time elected officials and, due to political reservations, 63% are women or from historically marginalised Scheduled Castes (SCs). Baseline data indicate limited knowledge about the schemes under their charge: the median WM knows only 40% of the required steps to implement schemes. Knowledge varies considerably—on 5 of 7 schemes, the bottom decile of WMs know 0 steps, while the top-decile of WMs know 60%—suggesting strong potential for learning from better-informed peers. Moreover, although most WMs report strong ties with other WMs within their GP, more than 80% report never having discussed work with a WM outside their GP.

Participation in the meetings is substantial: across the two in-person sessions and four conference calls, average attendance exceeds 70%. These interactions translate into new professional connections. At endline, treated WMs are 51 percentage

enabled Hjort et al. (2021) to evaluate the impact of disseminating information on policy effectiveness to mayors.

[2]GPs are the smallest administrative unit in India. In Bihar, a GP typically consists of 4–5 revenue villages. The next tier is the block (≈15 GPs), followed by the district (≈14 blocks).

[3]The experiment was designed to generate insights at scale (Muralidharan and Niehaus, 2017).

points more likely to report knowing a randomly selected WM from their peer group than control WMs (control WMs were assigned to fictitious groups that never met). Discussions are facilitated by trained moderators, who guide conversation but do not provide information. Note-takers record detailed minutes that document, for each issue: (a) the WM who raised it, (b) the relevant scheme, (c) the WMs offering solutions, and (d) the content of the solutions. Across six meetings, the average group discussed 7.2 issues and 18.1 solutions or best practices.

Our endline survey reveals that treated WMs learn substantially, with large spillovers to untreated peers. We measure learning across four domains: 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, treatment increases the knowledge index by 0.12 standard deviations (SD), driven primarily by gains in tacit and best-practice knowledge. Spillovers are sizable: untreated WMs in treated GPs experience a 0.08 SD increase. Given that each GP contains roughly ten spillover WMs, aggregate absolute learning among untreated peers potentially exceeds that among treated WMs themselves.

These learning gains are tightly linked to the content of discussions in the peer meetings. For each WM and scheme, we construct an exposure measure based on the number of best practices shared during meetings regarding that scheme. WMs with above-median exposure to best practices exhibit a 0.08 SD increase in scheme-specific knowledge; those with below-median exposure exhibit virtually no improvement. Spillover WMs display parallel patterns: a spillover WM learns more about a scheme when their treated peers were highly exposed to discussions of that scheme. Each treated WM with above-median exposure increases a spillover WM's knowledge by 0.021 SD ($p = 0.105$).

We next examine where spillovers arise. Learning gains are larger among spillover WMs who share a caste or religious identity with treated peers in their GP, and increase with the number of such treated peers. We also examine strategic considerations for information-sharing by looking at effects separately for rivalrous and non-rivalrous schemes. While direct treatment effects on learning are similar across the two sets of schemes, within-GP spillovers are driven primarily by non-rivalrous schemes. This pattern is consistent with strategic withholding of information within GPs for rivalrous schemes, while learning within peer groups - formed across GPs and therefore not subject to local quota constraints - remains

unaffected.

Taken together, the learning patterns suggest two channels of diffusion: first, treatment induces extra-GP links leading to knowledge diffusion across GPs, and second, existing homophilic ties of treated WMs causes knowledge-spillovers and diffusion within GPs.

We next turn to see how peer groups affect outcomes beyond learning, beginning by examining impacts on agency. We find that treatment increases WMs' agency, and these increases are directly linked to learning. We measure agency in two ways. First, WMs report greater confidence in implementing schemes: confidence rises by 0.1 SD, with gains concentrated among WMs whose peer groups exchanged more information. Second, we run a sub-experiment among treated and control WMs where they are offered the chance to collect signatures from peers on a petition to be forwarded to the Rural Development Department, Government of Bihar regarding devolving responsibilities to WMs. Here, we find that treated WMs are able to get 40% more signatures from other WMs. We also run another sub-experiment to measure adoption of new technologies: WMs were offered the chance to connect to a hotline to file complaints under a relatively new complaints system run by the Government of Bihar. While the overall treatment effects on complaint filing is zero, we find positive and significant effects for WMs with above median exposure to best practices.

The expansion of peer networks, learning, and agency is accompanied by expanded professional – political and bureaucratic – networks. Treated WMs report wider networks among WMs outside their GP. They are also more likely to report conferring with block-level bureaucrats and to report a connection to a political party. Our index of professional networks increases by 0.15 SD. Once again - and importantly - we find that these expansions are stronger among WMs in groups where more information was exchanged.

However, extra-GP professional expansion coincides with reduced interaction within the GP, particularly with the GP head. Treated WMs are 9 percentage points (15%) less likely to discuss work difficulties with the GP head, 8 percentage points (24%) less likely to attend Gram Sabha meetings, and 4 percentage points (27%) more likely to report a poor relationship with the GP head.

This friction with the GP head is significant, as the GP head plays a central role in project selection and service delivery. Prior work shows that GP heads can exercise hold-up power over development projects (Sharan and Kumar, 2025). These

concerns intensified after May 2023, when WMs lost financial control over water and sanitation infrastructure – the universe of public goods previously devolved to them. Thereafter, WMs' influence over public good provision flowed primarily through the Gram Panchayat Development Plan (GPDP) process. GPDPs are prepared annually in meetings involving the GP head, all WMs, and participating citizens. Once plans are approved by higher tiers of government, funds are allocated and implementation follows. The process operates with long lags: GPDP meetings for FY 2024–25 occurred between August and October 2023, with formal approvals issued in March 2024.

To examine effects on public good provision, we assemble project-level data for all GPs in FY 2024–25 using administrative records scraped from the state's online planning portal. This dataset covers the full universe of infrastructure projects mapped to each GP. To link outcomes to WMs' learning and actions, we focus on 18 schemes that WMs either campaigned on or discussed in meetings.

The results reveal two distinct effects. First, an *allocation effect*: treated GPs plan more projects and allocate approximately 5% more spending than control GPs. These effects are more concentrated in GPs where WMs acquired greater scheme-specific knowledge. Second, an *alignment effect*: the additional spending flows precisely toward schemes that citizens identify as priorities in our survey, and toward areas WMs reported campaigning on. Spending increases are negligible along schemes citizens did not prioritize or WMs did not campaign on. Together, these effects translate into real improvements: an independent audit we conduct of a sample of projects in mid-2025 finds that more than half of planned projects exist and many were under construction.

Despite these improvements, citizens do not update their perceptions. In our endline phone survey, citizens do not report better access to public goods or welfare schemes, nor do they rate treated WMs more favourably. Timing likely plays a key role: the citizen survey occurred in late 2024 – early 2025, when many projects were still being implemented. Our audit of projects suggests that only a quarter of the projects in the plans had been initiated at the time of the citizen survey. Moreover, for projects verified by the audit, citizens often attributed them to the GP head or local officials, rather than to their WM, suggesting that attribution frictions may limit voters' ability to recognise WMs' contributions.

Overall, our experiment demonstrates that peer networks can meaningfully strengthen the capabilities of local elected representatives, leading to more informed planning

and greater alignment with citizen priorities. The intervention itself is remarkably cost-effective: our back-of-the-envelope estimates indicate that each dollar spent on the programme yields approximately 18.47 US dollars in planned public goods and 9.42 US dollars in realised creation of public goods. Peer learning among politicians thus represents a scalable and economically attractive tool for improving governance in low-capacity environments.

Contribution to literature. Our study relates primarily to the literature on peer learning. Prior research shows that peers are an important source of information about best practices in many contexts. Farmers learn about new agricultural technologies from their neighbours (Foster and Rosenzweig, 1995; Conley and Udry, 2010). Borrowers spread information about microfinance loans (Banerjee et al., 2013). Teachers and salespeople learn effective practices from productive colleagues (Sandvik et al., 2020; Papay et al., 2020). Entrepreneurs share knowledge about pricing and suppliers with mentees and peers (Brooks et al., 2018; Iacovone et al., 2022; Fafchamps and Quinn, 2018). But there is little research on peer learning among politicians, even though politics is an important context and one where there is significant potential for peer learning, as many politicians have limited prior experience in government. Indeed, as countries decentralise power and broaden representation, it will become increasingly important to help new politicians learn how to govern.

Perhaps the closest paper to ours is Cai and Szeidl (2018), which studied the impacts of assigning Chinese small and medium enterprise (SME) managers to peer groups and found improvements in firm profits and management practices. We conduct a similar intervention for local politicians, which (to our knowledge) has not been evaluated before. Many countries have institutions that facilitate contact between local leaders, and our findings will shed light on their impacts. Data on meeting discussions and WhatsApp group chats also enable us to directly observe the spread of information through peer groups, which was not possible in Cai and Szeidl (2018). This enables us to show that learning and governance improvements on a particular scheme are largest when a group exchanges more information about that scheme. We also document that spillovers are present and large.

Most political economy papers examine the actions of individual politicians in isolation (Battaglini and Patacchini, 2019). Research on peer influence is thus limited to a few studies that explore how social ties between legislators in the US

Congress and European parliaments affect voting patterns (Harmon et al., 2019; Lowe and Jo, 2021) and co-sponsored legislation (Fowler, 2006; Canen et al., 2023; Battaglini et al., 2020). However, the focus of these studies is not on peer learning but other mechanisms, such as social pressure and vote-trading in legislatures, which are less relevant in our context. Our main contribution is to document whether and what politicians learn from their peers, and the impacts of peer learning on local governance and economic development.

Our study also contributes to a growing literature on policy diffusion. Economists have shown that policies diffuse due to academic research (Hjort et al., 2021), geographic proximity, partisan alignment (DellaVigna and Kim, 2022), electoral considerations (Bernecker et al., 2021; Shigeoka and Watanabe, 2023), formal systems of policy experimentation (Wang and Yang, 2023), and the rotation of bureaucrats across provinces (Lu, 2023). However, we do not know whether politician networks play an important role in spreading good policies and governance practices. Our study provides direct evidence on whether leaders learn best practices from their peers and sheds light on whether politician networks complement decentralisation, by diffusing successful local experiments to other local governments.

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 drain and lane construction (*Nali Gali*), solid waste management (*Lohiya Swachh Bharat Abhiyan*, LSBA), and the provision of tap water (*Nal Jal*) and solar lights.[4] 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) and toilet construction (*Swacch Bharat Abhiyaan*, SBM) programs. Not only do they have formal roles in these schemes, they are also perceived by citizens as the primary contact for scheme-related help, particularly for the implementation of the tap installation scheme (Table C13).

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, and work provided under the Mahatma Gandhi National Rural Employment Guarantee Scheme (NREGA). A substantial share of citizens rely on the WM as their primary contact for these schemes: 19% for subsidized food rations, 28% for NREGA, and 33% for subsidized housing (PMAY) (Table C13). 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.[5] 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

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

[5]Like 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.

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 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.

3 Theoretical Motivation: Scope for Peer Learning

Serving as a WM is an entry-level political position. 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.[6] 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 6).

[6]This 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.

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% (Table C5). 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 knowledge, they are able to piece it together collectively.[7]

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. When WMs interact primarily with other WMs within their own GP, much of the information they receive is filtered through the GP head, who may choose to disclose information selectively. Interacting with peers from other GPs can, therefore, help WMs better understand what is possible in their own relationship with the GP head — including alternative ways of negotiating, asserting their roles, and accessing resources.

Fourth, while WMs may benefit from peer learning in general, this channel may be particularly important for marginalized groups. Over half of WMs are women and about 20% are from Scheduled Castes (SCs), both of whom face social norms and structural barriers that limit access to information, resources, and political net-

[7]WMs 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.

works. Peer groups, therefore, have the potential to disproportionately benefit SC and female WMs by providing alternative channels for knowledge and support. However, we only estimate differential treatment effects by caste and not gender, because our pilot and baseline survey indicate that most female WMs attend peer groups with, or are entirely substituted by, a male relative.

Fifth, 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, at the start of the pandemic, WMs were suddenly asked to manage COVID-19 responses in their GPs, and anecdotal evidence suggests that discussions with peers helped them identify effective practices.

Despite this potential, baseline data show that 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.

4 Research Design

4.1 Intervention and Basic Methodological Framework

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 1 for a visual description of the sample.

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.

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

4.2 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 population[9]. The three additional districts increase representation of populations from the east[10] and the south[11]. 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 1), 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 C1). Panel A of Figure 5 shows that our experimental GPs cover a large share of the sampled districts.

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 C2).

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

[10] Purnia and Banka.

[11] Jehanabad.

[12] The 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.

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]

5 Data

We collect data along five key dimensions: knowledge, networks, agency, governance outcomes, and control variables. Below, we describe the data sources for each.

5.1 Knowledge

WMs' Knowledge We collect data on knowledge from the baseline (N = 7,277) and endline WM surveys (N = 6213). At baseline, we ask WMs to list the steps required to implement different schemes. At endline, we construct more sophisticated measures of knowledge. These include, across different schemes, questions capturing WMs' (i) formal and (ii) tacit knowledge regarding scheme implementation; (iii) procedural knowledge related to running schemes; and (iv) knowledge of best practices for problem-solving common local policy issues. The construction of these indices is detailed in Section G.1.

Knowledge Flow We designated note-takers who record the issues discussed in each meeting and the time spent discussing each issue. In a typical peer group meeting, about 6 issues are discussed, each for about 15 minutes. Most issues relate to scheme implementation or upward management of the Mukhiya and BDO.

[13] Panel B of Figure 5 plots one example group per district.

For each discussion topic, we identify (if any) the WM who raised the issue and the WM who offered a solution to the problem. Note-takers also briefly describe the problem and solution. [14]

For each WM, we can therefore calculate, for each scheme, the number of best practices they were exposed to and the time spent discussing these issues. In our eventual analysis, we are able to characterise WMs' as having above-median or below-median exposure to a scheme.

5.2 Networks

At baseline, we collect data on networks by asking WMs to name other WMs from their own GP, block, or district with whom they have work-related discussions. At endline, we complement this exercise with additional network measures. First, we ask WMs whether they know randomly selected members from their group (in the control arm, we ask about WMs from fictitious groups); this allows us to verify whether treatment led to participants getting to know one another. Second, we collect data on whom WMs discuss work-related problems with, expanding the choice set beyond other WMs. Third, we ask WMs to report interactions with higher-level bureaucrats, the GP head, and political parties.

5.3 Agency

We collect data on agency in three ways. First, using the baseline and endline WM surveys, we measure reported confidence by asking WMs to name up to two schemes they feel confident implementing. Second, we measure willingness to adopt new technologies by offering a randomly selected subset of treated and control WMs the opportunity to file complaints under Bihar's grievance redressal scheme. Third, we measure collective efficacy by assessing how randomly selected treated and control WMs vary in their ability to collect signatures on a petition demanding greater devolution.

[14] A problem might be: "*the Mukhiya 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 Mukhiya asking him to release funds.*" Alternatively, "*Petition the Block Development Officer, by writing a letter delivered with a copy to higher officials.*" In in-person meetings, we observed that WMs would occasionally discuss the exact contents of a letter to higher-level officials or exchange phone numbers of relevant officials when trying to resolve implementation snags.

5.4 Governance Outcomes

GPDP Data We obtain GPDPs from the eGramSwaraj portal.[15] These plans detail proposed expenditures across sectors for the subsequent financial year. We use GPDP data for the 2024 – 25 financial year, which coincides with the period of our intervention. These data allow us to examine planned spending priorities at the GP level.

NREGA Data We scraped 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 by caste and gender during our experimental period; and self-dealing by WMs and GP heads.[16]

Citizen Survey We survey 9,699 citizens (around two per ward from treatment and control areas and one per ward from spillover areas). The survey captures citizens' (i) assessments of public services in their ward; (ii) eligibility for, application to, and receipt of social welfare benefits; and (iii) views about their WM. The citizen survey was conducted over the phone and experienced low hit rates, owing to the fact that the phone numbers were from 2021 (four years prior to the survey) and were not tagged to wards.

5.5 Control Variables

Our control variables include baseline measures of knowledge and networks; caste and education of de facto WMs (as reported in the baseline survey); ward populations (from the Bihar State Election Commission); and GP-level characteristics (from Census 2011).

[15] eGramSwaraj is a user-friendly web-based portal launched by the Ministry of Panchayati Raj (MoPR) to strengthen e-Governance in Panchayati Raj Institutions (PRIs) across India.

[16] We 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 in corruption.

6 Empirical Analysis

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, C3 and C4 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 Table C3. 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 Table C3 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 C4 establishes balance over WMs' knowledge and pre-existing networks.

First Stage The intervention successfully increased peer connections. 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 first-stage effect confirms that the intervention substantially expanded cross-GP peer networks (additional results on politician peer networks are reported below).

7 Results

7.1 Learning

Direct effects. Our first main finding is that the intervention significantly improved learning among treated WMs. We measure WM knowledge at endline using four indices, which we combine into an overall index. 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.

Panel A of 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. 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.

Next, to provide more direct evidence that learning gains are driven by the content of peer-group discussions, we examine treatment heterogeneity based on a measure of the quality of the group discussion. For each group and each scheme, we compute the number of best practices discussed which we use as a proxy for the quality and richness of the group discussions. We then estimate heterogeneous treatment effects based on whether a group the number of best practices shared

within a group,lies above the median of this scheme-specific distribution. [17]

We find strong evidence that learning gains are larger in groups that exchange higher-quality information (Panel B of Table 2). In particular, the scheme-specific combined knowledge index increases by 0.08 SD for ward members in groups with an above-median number of best practices shared, while we find no detectable gains for groups below the median.[18].

Learning and WhatsApp groups. We use text messages exchanged via *WhatsApp* to construct an additional measure of the quality of peer interactions. In Appendix Section E, we show that groups that exchange more messages via WhatsApp exhibit greater learning. In Tables E1 and E2, we measure, as in the case of meetings, learning at the WM x scheme level. Consistent with the results for in-person meetings/conference-calls, groups that exchange more messages about a given scheme exhibit greater learning on that scheme.[19]

Spillover Effects. We also find sizeable spillover effects (Table 3). As shown in Panel A, the spillover effect on the combined knowledge index is approximately 0.08 standard deviations, amounting to nearly two-thirds of the direct treatment effect. Given that each GP contains roughly ten spillover WMs, aggregate learning among untreated peers may exceed that among treated WMs themselves. We also find suggestive evidence that spillovers are larger for WMs whose treated peers participated in groups that shared a greater number of best practices, mirroring the pattern observed for the direct treatment effects (see Panel B of Table 3). To capture this heterogeneity, we count, for each spillover WM, how many treated WMs in the same GP were in groups that exchanged above-median numbers of best practices. The interaction between spillover status and this measure is positive but only marginally significant (p-value = 0.103).

We next explore whether strategic considerations help explain the magnitude of spillover effects. In particular, WMs may have incentives to limit information

[17] In the appendix, we report results based on a second dimension of meeting quality - the intensity of information exchange, measured by the total amount of time each group spends discussing a given scheme. We again estimate heterogeneous effects by classifying groups as above or below the median in scheme-specific discussion time.

[18] This estimate is not directly comparable to the treatment effects in reported in Panel A, as it is estimated at the scheme level and then aggregated across schemes.

[19] The interaction of treatment with the binary measure of above-median message exchange has a p-value of 0.168 (Table E1). 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 E2).

sharing on schemes for which resources are effectively constrained at the GP level, such that increased access in one ward reduces availability in others. We classify these as rivalrous schemes, which include *Nal Jal*, *Nali Gali*, and NREGA.

We examine whether spillovers are weaker for rivalrous schemes and find suggestive, though noisy, evidence consistent with this pattern (Figure 3).[20] For both rivarous and non-rivalrous schemes, the direct on knowledge are positive and statistically significant. However, when examining spillovers, we find that the effects to be positive for non-rivalrous schemes and negative for rivalrous schemes. While the spillover effects in both cases are statistically indistinguishable from zero, this pattern is consistent with strategic withholding of information within GPs for rivalrous schemes, while learning within peer groups - formed across GPs and therefore not subject to local quota constraints - remains unaffected.

We also find evidence that spillover effects are stronger among spillover WMs who share social identity with treated peers in their GP, and that these effects increase with the number of such treated peers (Table 4). 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. These patterns are concentrated among treated peers who participated in groups with above-median numbers of best practices shared, indicating that identity-based ties facilitate the within-GP diffusion of information acquired through peer meetings.

Heterogeneous effects of politician networks. In this section, we estimate treatment effect heterogeneity using machine-learning based methods, specifically the causal forests method of Wager and Athey (2018). We estimate conditional average treatment effects (CATEs) for our key outcome—the knowledge index.

Figure D1a 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 histogram lies above 0.

Figure D1b presents the 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.

[20] The corresponding tables can be found in the Appendix.

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.

Who Benefits from Networks? We analyse correlates of the direct and spillover CATEs. Panel (a) of Figure D2 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, more advantaged WMs benefitted more from the intervention. In line with this, table C32 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 they matter less than individual characteristics.[21]

Panel (b) of Figure D2 presents correlates of spillover effects. Here we see less 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.

7.2 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 tasks[22], (ii) their ability to mobilize signatures for a petition, and (iii) their willingness to use the grievance redressal system to address service delivery issues in their constituency.

Confidence. Peer learning 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 standard deviations higher than control WMs on a standardized index captur-

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

[22] See Section G.3.

ing confidence across multiple schemes (Panel A, Table 5). These gains are concentrated among peer groups that exchange more information: WMs in groups with below-median levels of best-practice exchange do not experience significant improvements in confidence. By contrast, treatment effects rise to 0.18 standard deviations among WMs in groups with above-median best-practice sharing. This pattern suggests that peer engagement facilitates meaningful learning that translates into greater self-efficacy.

Collective Action. Our second domain of agency is collective political behaviour, and we implement a sub-experiment on collective action. Approximately 790 randomly selected WMs were offered the opportunity to lead a petition on a governance issue. Specifically, we contacted WMs and invited them to organize a petition on one of two issues: (i) restoring WMs' role in managing *Nal-Jal* (tap water) projects in their wards, or (ii) granting WMs greater autonomy in NREGA implementation. We then measure the number of signatures each WM mobilized.

We find that treated WMs—those assigned to peer groups - are 7.7 percentage points more likely to mobilize at least one signature, representing a 40% increase relative to the baseline (Column 2 Panel B, Table 5). They are also 6.1 percentage points more likely to mobilize a signature from another WM (Panel B, Column 3). The total number of signatures mobilized also doubles (Column 1). We find no evidence that treated and control WMs differ in their beliefs about the importance of the issue underlying the petition (Column 4), suggesting that these effects are not driven by differential perceptions of issue salience. Instead, the results are consistent with the intervention increasing WMs' capacity to mobilize others, reflecting increased agency arising from participation in peer groups.

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

We measure whether informed WMs acted on this information by filing a com-

plaint. Overall, we find no evidence that treated WMs—those assigned to peer groups—are more likely to file a complaint. However, treated WMs in groups that exchanged more information are significantly more likely to do so (Table 5, Panel C).

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.

7.3 Professional Networks

Beyond learning and agency, the intervention also shaped the professional and political networks of treated WMs. As detailed in the appendix (see Section G.2), we construct three network indices capturing: (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.

Treated WMs exhibit stronger networks across all measures (Panel A, Table 6). 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 (0.06 SD) and political networks (0.05 SD).

As with learning, these gains are concentrated among WMs whose peer groups exchanged higher-quality information. The treatment effect on the combined network index is 0.17 standard deviations for WMs in above-median best-practice groups, while effects are statistically indistinguishable from zero for those in below-median groups (Panel B, Table 6). This pattern mirrors the heterogeneity observed for knowledge gains, suggesting that richer peer interactions facilitated not only learning but also the formation of durable professional ties.

7.4 Conflict

An important feature of the intervention is that it expands WMs' professional networks beyond the GP, increasing their exposure to ward members from other GPs, block-level officials, and political actors. These new external ties may alter local power dynamics within the GP—particularly given that WMs have limited formal

financial authority and the GP Head retains primary responsibility for project execution. Prior work documents persistent tensions between ward members and GP Heads (Sharan, 2021), a pattern also reflected in our field notes from peer meetings.

We find that the intervention intensifies these 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. Consistent with this, they are less likely to attend Gram Sabha meetings (Table 7).

These patterns suggest that increases in knowledge and confidence may also disrupt existing hierarchies and working relationships within the GP. The coexistence of professional gains and heightened conflict raises an important question, one which we turn to next: how do these opposing forces shape downstream 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 execution.

7.5 Overall Impacts on Governance

We now examine whether the intervention translated into improved service delivery, turning first to the GPDP dataset. Recall that the GPDP data record planned GP spending across government schemes for the financial year 2024 – 25. While the GPDP does not assign projects to individual wards, the presence of substantial within-GP spillovers in learning motivates an analysis of GP-wide outcomes. Accordingly, we test whether treated GPs exhibit improvements in overall scheme planning.

From the GPDP dataset, we create two outcome measures: first, the total number of projects on a scheme in a GP; second, the total amount spent on a scheme in a GP.

Turning to treatment effects, we find that treated GPs plan more ambitiously. They plan, on average, 0.76 additional projects (a 5.4% increase) and allocate INR 230,000 more in total spending (a 4.6% increase) relative to control GPs (Table 8, Panel A).

Learning-linked Effects. We next assess whether these planning gains reflect the learning generated during peer meetings. Specifically, we test whether schemes that were discussed more intensively – or for which more best practices were exchanged – receive greater planned investment. We conduct this analysis at the GP-scheme level, estimating heterogeneous treatment effects based on whether a

GP has an additional treated WM who came from a group that exchanged above-median number of best practices on that scheme.

The results are consistent with learning-driven effects (Table 8, Panel B). On average, control GPs plan 1.83 projects per scheme; each additional above-median treated WM increases planned projects by 0.062 (3.4%; Column 1).

Campaign promises and citizen preferences. More ambitious planning need not be welfare-improving if it fails to reflect citizens' needs. We therefore examine whether GPDP plans align with WMs' campaign promises and citizen preferences.

For campaign promises, we compute – at the GP-scheme level – the share of WMs who reported campaigning on a given scheme and interact this with treatment status (Table 9, columns 1 and 2). Even in control GPs, schemes supported by a larger share of campaigning WMs receive more projects and higher planned spending. The interaction with treatment is positive and statistically significant for both the number of projects and the amount planned to be spent. The coefficient on the *Treated GP* variable is zero, implying that when no WM campaigned on a scheme, we find no additional planned spending in treated GPs.

A similar pattern emerges for citizen preferences. For each scheme, we calculate the share of surveyed citizens who express a preference for spending on that scheme. The positive relationship between citizen support and planned projects present in control GPs strengthens substantially in treated GPs, with both the number of projects and planned expenditure rising sharply with citizen demand (Table 9, columns 3 and 4). As before, we find little evidence of additional spending – even in treated GPs – on schemes for which no citizen expresses a preference. Together, these results suggest that treated WMs plan more ambitiously precisely where their constituents want them to.

8 Validation and Robustness

Predicting Learning Our main learning results demonstrate that groups exchanging more best practices exhibit stronger learning outcomes at endline. Since best-practice exchange is a post-treatment variable, we now predict learning at the group level using baseline characteristics alone. This exercise sheds light on two related questions: first, how predictable is learning across groups? Second, can group composition predict meeting quality in ways that matter for learning?

To this end, we use 142 baseline predictors measured at the individual, group, ward, and GP levels to predict meeting quality. 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 across peer meetings for 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.[23] Prediction proves difficult: the R^2 is 0.006, indicating that the model captures negligible variation in solutions. Table C25 presents the results. Groups predicted to exchange more solutions exhibit significantly greater learning: the combined index rises by 0.053 SD ($p < 0.05$) for such groups.

Second, we estimate a cross-validated LASSO on the residualized predictors. The model's predictive power remains limited, with an R^2 of 0.004. Nonetheless, groups with above-median predicted solutions display 0.038 SD greater learning as measured by the combined index ($p = 0.12$), as reported in Column 6 of Table C26.

Taken together, these results point to two conclusions: meeting dynamics are largely unpredictable from baseline characteristics alone, yet to the extent that meeting quality can be predicted, it is positively correlated with learning outcomes at endline.

Robustness All regressions employ controls selected via double-selection LASSO. In the appendix, we demonstrate robustness to omitting all controls (Table C27), to re-clustering standard errors at the peer group level (Table C28), and to alternative definitions of the learning outcome. In our main specifications, a WM is coded as exposed to a best practice if it was discussed in a meeting they attended; we show this result is robust to excluding solutions proposed by the WM themselves (Table C29).

Attrition We successfully re-surveyed 85% of the baseline sample at endline (N=6,213); attrition handling is described in Section F. To assess whether attrition introduces bias, we first examine who drops out. Attrited and non-attrited respondents are broadly similar across baseline characteristics, with one exception: SC WMs are

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

somewhat more likely to be located at endline (Table C21). Crucially, however, treatment, control, and spillover WMs observed at endline are balanced on baseline variables. Our results are further robust to doubly robust estimators that explicitly account for attrition (Table F1). Lee bounds analysis reveals that while upper bounds are large and statistically significant, lower bounds are predominantly positive, albeit not always significant (Table F3).

9 Discussion

In this section, we focus on two outcomes: first, our citizen survey of over 9600 households conducted over the phone. Here, we study if treatment improves citizens' reported experience of access to public goods and welfare in our phone survey. We then turn to the effects on corruption and rent-seeking.

9.1 Reported citizen welfare.

We consider two sets of outcomes: citizen ratings of public goods and services, and reported access to welfare schemes (Table C30). We find no statistically significant effects on either dimension. As noted earlier, however, the citizen survey suffered from very low response rates due to phone numbers dating from 2021, which limits our ability to detect downstream effects at the ward level.

9.2 Explaining the Divergence: Governance Improvements Take Time

One potential explanation for the absence of detectable impacts in the citizen survey is timing. While the intervention led to improvements in planning and learning, these gains may not 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 2). However, GPDP plans pertain to the 2024 – 25 financial year, and implementation of planned projects often occurs later in the cycle. Because the GPDP data do not record implementation dates, 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. Among projects that were found, more than half were constructed after the completion of the citizen endline survey (see Figure 4).

These findings indicate that a substantial share of implementation occurred after the period in which citizen outcomes were measured. Moreover, as Table C19 shows, even when projects are built, citizens are as likely to attribute it to WMs as they are to the GP head.[24] As a result, the null effects observed in the citizen survey – both for average outcomes and for wards where WMs exhibited greater learning – are consistent with delayed implementation rather than an absence of governance improvements. In other words, plans take time to be implemented.

9.3 Corruption and Rent-Seeking

A natural concern with peer learning among politicians is that it may enable officials to extract rents more effectively – a particularly salient concern in Bihar (Banerjee et al., 2020). We test for this using two complementary approaches: administrative data on NREGA work histories, which we use to detect self-dealing, and citizen reports of bribe-taking from our endline survey.

NREGA self-dealing. We match WMs to individuals in the NREGA administrative data using names and family identifiers, successfully identifying approximately 15.7% of WMs across experimental GPs. 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 C31, 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).

Bribe-taking. In our endline citizen survey, we ask respondents whether they accessed any of five major welfare programmes during the intervention period

[24] Indeed, while WMs are attributed to be responsible for project implementation in 36.1% of the cases (Table C18), when asked who was the main actor responsible, citizens attribute it to the WM only 20% - not sure where this estimate is from of the time.

(NREGA, rations, pensions, toilets, and housing), and test whether citizens in treated wards are more likely to 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 C31, Panel B, column 6).

Taken together, evidence from both administrative data and citizen surveys suggests that the intervention did not meaningfully affect corruption or rent-seeking behaviour.

10 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 treatment effect on GP-level spending, the intervention is projected to generate a total planned increase in public expenditure of INR 222.9 million (USD 2.47 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 ultimately implemented. Under this adjustment, the realised increase in public spending equals INR 113.7 million (USD 1.26 million). Even under this conservative assumption, the intervention yields approximately USD 9.4 in additional public spending for every dollar spent on programme implementation.

11 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 increase their procedural, tacit, and best-practice knowledge of governance. These learning gains spill over to untreated peers within the same village councils and are concentrated in groups that exchange more substantive information. Increased knowledge translates into higher confidence and agency, and ultimately into better governance: treated councils plan more projects and allocate more spending, with increases closely aligned with cit-

izen priorities and politicians' campaign commitments.

The results have clear policy implications for low-capacity settings. Rather than relying solely on formal training or top-down oversight, governments can strengthen local governance by facilitating horizontal learning among elected representatives. 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 18 in planned public spending and over USD 9 in realised public-good creation. Together with the presence of large spillovers, this makes peer networks a particularly 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.

References

Banerjee, Abhijit, Arun G Chandrasekhar, Esther Duflo, and Matthew O Jackson, "The diffusion of microfinance," *Science*, 2013, *341* (6144), 1236498.

_ , Esther Duflo, Clement Imbert, Santhosh Mathew, and Rohini Pande, "E-governance, accountability, and leakage in public programs: Experimental evidence from a financial management reform in India," *American Economic Journal: Applied Economics*, 2020, *12* (4), 39–72.

Battaglini, Marco and Eleonora Patacchini, "Social networks in policy making," *Annual Review of Economics*, 2019, *11*, 473–494.

_ , Valerio Leone Sciabolazza, and Eleonora Patacchini, "Effectiveness of connected legislators," *American Journal of Political Science*, 2020, *64* (4), 739–756.

Beaman, Lori, Ariel BenYishay, Jeremy Magruder, and Ahmed Mushfiq Mobarak, "Can network theory-based targeting increase technology adoption?," *American Economic Review*, 2021, *111* (6), 1918–1943.

Bernecker, Andreas, Pierre C Boyer, and Christina Gathmann, "The role of electoral incentives for policy innovation: Evidence from the us welfare reform," *American Economic Journal: Economic Policy*, 2021, *13* (2), 26–57.

Brooks, Wyatt, Kevin Donovan, and Terence R Johnson, "Mentors or teachers? Microenterprise training in Kenya," *American Economic Journal: Applied Economics*, 2018, *10* (4), 196–221.

Cai, Jing and Adam Szeidl, "Interfirm relationships and business performance," *The Quarterly Journal of Economics*, 2018, *133* (3), 1229–1282.

Canen, Nathan, Matthew O Jackson, and Francesco Trebbi, "Social interactions and legislative activity," *Journal of the European Economic Association*, 2023, *21* (3), 1072–1118.

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

Conley, Timothy G and Christopher R Udry, "Learning about a new technology: Pineapple in Ghana," *American economic review*, 2010, *100* (1), 35–69.

DellaVigna, Stefano and Woojin Kim, "Policy diffusion and polarization across US states," Technical Report, National Bureau of Economic Research 2022.

Duflo, Esther, Pascaline Dupas, and Michael Kremer, "Peer effects, teacher incentives, and the impact of tracking: Evidence from a randomized evaluation in Kenya," *American economic review*, 2011, *101* (5), 1739–1774.

Fafchamps, Marcel and Simon Quinn, "Networks and manufacturing firms in Africa: Results from a randomized field experiment," *The World Bank Economic Review*, 2018, *32* (3), 656–675.

Foster, Andrew D and Mark R Rosenzweig, "Learning by doing and learning from others: Human capital and technical change in agriculture," *Journal of political Economy*, 1995, *103* (6), 1176–1209.

Fowler, James H, "Connecting the Congress: A study of cosponsorship networks," *Political analysis*, 2006, *14* (4), 456–487.

Harmon, Nikolaj, Raymond Fisman, and Emir Kamenica, "Peer effects in legislative voting," *American Economic Journal: Applied Economics*, 2019, *11* (4), 156–180.

Hjort, Jonas, Diana Moreira, Gautam Rao, and Juan Francisco Santini, "How research affects policy: Experimental evidence from 2,150 brazilian municipalities," *American Economic Review*, 2021, *111* (5), 1442–1480.

Iacovone, Leonardo, William Maloney, and David McKenzie, "Improving management with individual and group-based consulting: Results from a randomized experiment in colombia," *The Review of Economic Studies*, 2022, *89* (1), 346–371.

Kling, Jeffrey R, Jeffrey B Liebman, and Lawrence F Katz, "Experimental analysis of neighborhood effects," *Econometrica*, 2007, *75* (1), 83–119.

Lee, David S, "Training, Wages, and Sample Selection: Estimating Sharp Bounds on Treatment Effects," *The Review of Economic Studies*, 2009, *76* (3), 1071–1102.

Lowe, Matt and Donghee Jo, "Legislature Integration and Bipartisanship: A Natural Experiment in Iceland," 2021.

Lu, Jiaxuan, "Leadership rotations and the convergence of subnational economic policies in China: evidence from provincial government work reports," *Forthcoming, Journal of Law, Economics, and Organization, https://doi.org/10.1093/jleo/ewac026*, 2023.

Muralidharan, Karthik and Paul Niehaus, "Experimentation at scale," *Journal of Economic Perspectives*, 2017, *31* (4), 103–124.

Papay, John P, Eric S Taylor, John H Tyler, and Mary E Laski, "Learning job skills from colleagues at work: Evidence from a field experiment using teacher performance data," *American Economic Journal: Economic Policy*, 2020, *12* (1), 359–388.

Sandvik, Jason J, Richard E Saouma, Nathan T Seegert, and Christopher T Stanton, "Workplace knowledge flows," *The Quarterly Journal of Economics*, 2020, *135* (3), 1635–1680.

Scharfstein, Daniel O, Andrea Rotnitzky, and James M Robins, "Adjusting for nonignorable drop-out using semiparametric nonresponse models," *Journal of the American Statistical Association*, 1999, *94* (448), 1096–1120.

Sharan, MR, *Last Among Equals: Power, caste and politics in Bihar's villages*, Westland Publications, 2021.

_ **and Chinmaya Kumar**, "Something to complain about: How minority representatives overcome ethnic differences," Technical Report, Mimeo, University of Maryland 2025.

Shigeoka, Hitoshi and Yasutora Watanabe, "Policy Diffusion Through Elections," Technical Report, National Bureau of Economic Research 2023.

Wager, Stefan and Susan Athey, "Estimation and inference of heterogeneous treatment effects using random forests," *Journal of the American Statistical Association*, 2018, *113* (523), 1228–1242.

Wang, Shaoda and David Y Yang, "Policy experimentation in China: The political economy of policy learning," Technical Report, National Bureau of Economic Research 2023.

A Main Tables

Table 1. Balance across Treatment and Control GPs.

Variable	(1) Control	(2) Treatment	(3) Difference
Proportion of SCs (Census 2011)	0.169	0.167	-0.002
	(0.090)	(0.088)	(0.003)
Distance to District Headquarters (Census 2011)	30.270	30.518	0.438
	(13.569)	(13.677)	(0.576)
Total GP Area (Census 2011)	1,053.301	1,042.428	-5.607
	(645.286)	(643.745)	(25.640)
Total Population of GP (Census 2011)	12,455.464	12,426.564	25.663
	(5,232.069)	(5,165.761)	(221.380)
Number of Villages in GP (Census 2011)	5.033	5.101	0.020
	(4.229)	(4.152)	(0.151)
Percentages of SCs in Main SC Village (Census 2011)	0.600	0.593	-0.005
	(0.249)	(0.242)	(0.010)
SC Reserved	0.166	0.173	0.006
	(0.372)	(0.379)	(0.016)
ST Reserved	0.003	0.007	0.004
	(0.055)	(0.081)	(0.003)
EBC Reserved	0.166	0.176	0.009
	(0.372)	(0.381)	(0.016)
Gender Reserved	0.444	0.461	0.018
	(0.497)	(0.499)	(0.022)
Total Educational Facilities (Census 2001)	3.470	3.458	-0.031
	(2.043)	(1.973)	(0.077)
Primary Health Sub Centres (Census 2001)	0.444	0.405	-0.039
	(0.700)	(0.664)	(0.029)
Post Office (Census 2001)	1.074	1.082	0.005
	(0.806)	(0.813)	(0.035)
Bank Facilities (Census 2001)	0.338	0.354	0.016
	(0.630)	(0.650)	(0.028)
Power Supply (Census 2001)	1.799	1.763	-0.042
	(1.857)	(1.943)	(0.080)
Paved Road (Census 2001)	1.759	1.726	-0.045
	(1.634)	(1.621)	(0.069)
Mud Road (Census 2001)	4.096	4.137	0.027
	(3.097)	(3.100)	(0.118)
Child Welfare Centre (Census 2001)	0.054	0.035	-0.019
	(0.546)	(0.294)	(0.018)
Bus facilities (Census 2001)	0.510	0.543	0.031
	(0.907)	(0.945)	(0.040)
Mean Village Income (Census 2001)	415342.969	366579.094	-42466.250
	(4.827e+06)	(3.172e+06)	(168499.312)
Mean Village Expenditure (Census 2001)	928866.125	255508.781	-6.291e+05
	(2.116e+07)	(2.111e+06)	(552296.688)
Observations	1,301	912	2,213

Note: This table displays balance between treatment and control GPs from the experiment. Figures in parenthesis are standard errors. P values: * 0.1 ** 0.05 *** 0.01.

Table 2. **Impact of Treatment on Learning Outcomes and Heterogeneity by 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 Index (std)
Panel A: Treatment Effect					
Treatment Ward	0.0428	0.0670**	0.1413***	0.1003***	0.1268***
	(0.0307)	(0.0309)	(0.0311)	(0.0313)	(0.0311)
Observations	4415	4415	4415	4415	4415
	Index for each WM at the Scheme level				
Panel B: Heterogeneity by Above Median Best Practices					
Treatment Ward	-0.0351	0.0133	-0.0025	-0.0050	-0.0069
	(0.0308)	(0.0305)	(0.0297)	(0.0217)	(0.0226)
Above Median Best Practices	0.0879***	0.0330	0.0439	0.0725***	0.0804***
	(0.0283)	(0.0305)	(0.0326)	(0.0221)	(0.0211)
Observations	17636	14312	12715	26454	33085
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: Panel A reports the main treatment effect of being in a treatment ward on learning outcomes. Panel B examines heterogeneity by meeting quality. A ward member is classified as having above median best practices if the total number of best practices discussed in their meeting exceeds the median across all meetings. All indices are standardised using the control mean. Controls for both the panels are determined using double select lasso. The controls for panel A include baseline knowledge, confidence, education, age and dummies that control for access to local bureaucrats and connectivity through phone. Panel A also accounts for district fixed effects. The controls for Panel B include all of the above controls as well as baseline networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, if ward member recieved training and additional dummies that control for access other local bureaucrats. Panel B controls for both district and scheme 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 Learning Outcomes and Heterogeneity by 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 Index (std)
Panel A: Spillover Effect					
Spillover Ward	0.0350	0.0369	0.0861**	0.0969***	0.0844**
	(0.0342)	(0.0335)	(0.0417)	(0.0349)	(0.0360)
Observations	4012	4012	3266	4012	4012
	Index for each WM at the Scheme level				
Panel B: Heterogeneity by Above Median Best Practices					
Spillover Ward	0.0030	0.0052	-0.0421	0.0361	0.0199
	(0.0371)	(0.0364)	(0.0504)	(0.0260)	(0.0274)
Count of WM Above Median Best Practices in GP	0.0179	0.0198	0.0491*	0.0104	0.0210
	(0.0173)	(0.0177)	(0.0253)	(0.0124)	(0.0129)
Observations	16184	13096	7718	24276	30311
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: Panel A reports the main spillover effect of being in a spillover ward on learning outcomes. Panel B examines heterogeneity by the number of ward members in the GP who participated in meetings where above median best practices were discussed. All indices are standardised using the control mean. Controls for both the panels are determined using double select lasso. The controls for panel A include baseline knowledge, confidence, education, age and dummies that control for access to local bureaucrats and connectivity through phone. Panel A also accounts for district fixed effects. The controls for Panel B include all of the above controls as well as baseline 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. Panel B controls for both district and scheme 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 4. **Spillover Effects on Combined Learning Index by Social Groups**

Index for each WM at Scheme level	(1) **Combined Learning Index (std)**	(2) **Combined Learning Index (std)**
Spillover Ward	0.0200	0.0209
	(0.0274)	(0.0275)
WM Count: Above median Best Practices & same caste in GP	0.0434**	
	(0.0211)	
WM Count: Above median Best Practices & diff. caste in GP	0.0123	
	(0.0147)	
WM Count: Above median Best Practices & same religion in GP		0.0236*
		(0.0133)
WM Count: Above median Best Practices & diff. religion in GP		0.0055
		(0.0270)
Observations	30311	30311
WM level controls	Yes	Yes
Ward level controls	Yes	Yes
Cluster	UGP	UGP
Control mean	0	0

Notes: The above table spillover effects on overall learning index by social group. Column (1) shows spillover effects by the count of 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 ward members who blong to same/different religion as the ward member in a GP. 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 recieved 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 5. **Impact of Treatment on Confidence, Collective Action, and Grievance Redressal**

	(1) Confidence Index (std)	(2) Confidence Index (std)		
Panel A: Confidence				
Treatment Ward	0.090***	-0.009		
	(0.032)	(0.040)		
Treat × Above Median Best Practices		0.188***		
		(0.050)		
Observations	4413	4413		
Ward-Level Controls	No	No		
Control Mean	0	0		
Panel B: Collective Action				
	No. Signed	**Any Signed**	**Any WM Signed**	**Petition Imp.**
Treatment Ward	0.343*	0.077**	0.061*	0.006
	(0.191)	(0.039)	(0.036)	(0.057)
Observations	618	619	618	617
Ward-Level Controls	Yes	Yes	Yes	Yes
Control Mean	.329	.184	.165	4.71
Panel C: Grievance Redressal				
	Grievance Filed	**Grievance Filed**		
Treatment Ward	0.011	-0.027		
	(0.025)	(0.027)		
Treat × Above Median Best Practices		0.066*		
		(0.037)		
Observations	492	492		
Ward-Level Controls	No	No		
Control Mean	.075	.075		

Notes: Panel A reports the impact of treatment on the confidence index (standardised using the control mean). Column 1 shows the baseline treatment effect; Column 2 adds heterogeneity by above median best practices discussed in meetings. Panel B reports the effect of treatment on signatures mobilised for collective action, with controls determined by double select lasso. All columns control for baseline knowledge and column (1) and (3) control for knowledge as well as block level networks. Panel C reports the effect of treatment on grievance filing among ward members informed of the information treatment. A 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. Panels A and C report regressions without controls as determined using the optimal double select lasso model. Each panel controls for district fixed effects. Standard errors clustered at the UGP level and are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6. **Effects of Treatment on Ward Member Networks and Heterogeneity by Above Median Best Practices**

	(1)	(2)	(3)	(4)
	Outside-GP WM Network (std)	**Block-Level Bureaucrat Networks (std)**	**Pol-Party Network (std)**	**Combined Index (std)**
Panel A: Treatment Effect				
Treatment Ward	0.1531***	0.0681**	0.0487*	0.1529***
	(0.0359)	(0.0327)	(0.0295)	(0.0332)
Observations	4408	4408	4392	4408
Panel B: Heterogeneity by Above Median Best Practices				
Treatment Ward	0.0366	0.0297	0.0305	0.0614
	(0.0430)	(0.0404)	(0.0379)	(0.0397)
Treat × Above Median Best Practices	0.1890***	0.0720	0.0341	0.1715***
	(0.0577)	(0.0467)	(0.0444)	(0.0510)
Observations	4408	4408	4392	4408
Ward-Level Controls	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0

Notes: Panel A reports the main treatment effect on ward member network outcomes. Panel B examines heterogeneity by above median best practices discussed in meetings. A 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. All outcome indices are standardized using the control group mean and standard deviation. Controls include baseline networks, 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. Controls are 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 7. **Effect of Treatment on Conflict and Relationships with GP Level Bureaucrats & Politicians**

	(1)	(2)	(3)	(4)	(5)
	Conflict Rozgar Sevak	**Conflict PS**	**Conflict GP Head**	**Bad Relationship GP Head**	**Attend 4 Village Meet At Least**
Treated Ward	0.0085**	0.0137**	0.0132**	0.0452***	-0.0764***
	(0.0040)	(0.0063)	(0.0062)	(0.0119)	(0.0144)
Observations	4663	4663	4663	4641	4346
WM Controls	No	No	No	No	No
Ward Level Controls	No	No	No	No	No
Control Mean	.013	.037	.038	.15	.339

Notes: The above table reports the effect of treatment on conflicts and relationships with local bureaucrats and politicans. Each regression controls for district fixed effects. The table reports results 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 8. **Effects of Treatment on GPDP Planned Activities and Estimated Costs, and Heterogeneity by Above Median Best Practices**

	(1) **Projects (Count)**	(2) **Projects (Count)**	(3) **Estimated Cost (Absolute)**	(4) **Estimated Cost (Absolute)**
Panel A: GP-Level Baseline				
Treated GP	0.7665**	0.7593**	231753.3067***	229014.6292***
	(0.3217)	(0.3207)	(82939.1257)	(82174.3458)
Observations	2158	2158	2158	2158
GP-Level Controls	No	Yes	No	Yes
Control Mean	14.489	14.489	5002000	5002000
	Projects in each GP at the Scheme Level			
Panel B: Heterogeneity by Above Median Best Practices				
Treated GP	-0.016	-0.015	32533.124	31715.661
	(0.068)	(0.068)	(21816.454)	(21717.760)
Treat × WMs in Above Median Best Practices	0.064**	0.063*	4176.981	4354.768
	(0.032)	(0.033)	(9835.113)	(9774.618)
Observations	19422	19422	19422	19422
GP-Level Controls	No	Yes	No	Yes
Control Mean	1.838	1.838	702093.813	702093.813

Notes: Panel A reports the baseline GP-level treatment effect on planned GPDP activities and estimated costs. Panel B examines heterogeneity at the GP × scheme level by whether ward members participated in meetings where above-median best practices were discussed. Outcomes in Panel A are measured at the Gram Panchayat level; Panel B outcomes are at the GP × scheme level and includes schemes Naljal, Naligali, NREGA, Solarlights, Toilet (Shauchalya), LSBA, Pension and Ration. Estimated cost outcomes are in absolute monetary units. GP-level controls for count of projects in Panel A include total population. In panel B, controls for count of projects include total population, number of villages, total area, distance from district HQ, distance from nearest town and proportion of SC citizens in the GP. For estimated cost, Panel A controls include total population and Panel B controls include total population and distance from nearest town. All controls are determined by double select lasso. All regressions control for district fixed effects and Panel B control for both district and scheme fixed effects. Robust standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

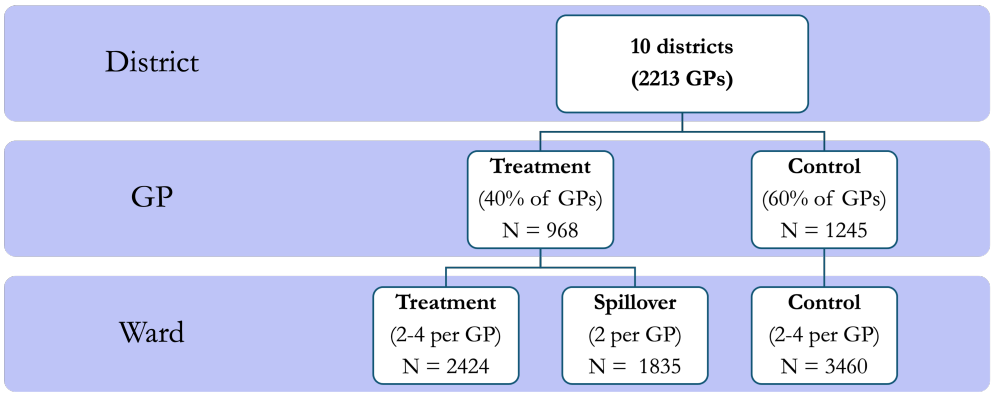
Table 9. **Effects of Treatment Heterogeneity, Ward Member Campaign & Citizen Preferences on GPDP Planned Activities and Estimated Costs**

	Projects in each GP at the Scheme Level			
	(1) **Total Projects (Count)**	(2) **Estimated Cost (Absolute)**	(3) **Total Projects (Count)**	(4) **Estimated Cost (Absolute)**
Treated GP	-0.0157	240.6163	0.0108	1066.7040
	(0.0441)	(10834.0959)	(0.0183)	(5031.2633)
Prop. WM Campaigned on Scheme j	0.3228***	96145.0195***		
	(0.1020)	(34623.7654)		
Treated GP × Prop. WM Campaigned on Scheme j	0.4638**	165342.6824***		
	(0.1905)	(64000.0080)		
Citizen Share (Pref j)			0.3304**	67612.5084
			(0.1356)	(47672.1933)
Treated GP × Citizen share (pref. j)			0.5907**	238662.0262***
			(0.2380)	(81182.9116)
Observations	17208	17208	35802	35802
GP Level Controls	Yes	Yes	Yes	Yes
Control Mean	1.89	742978.62	1.01	372046.329

Notes: The first two columns show the effects of being from a treated GP and having a larger share of ward members in the GP campaigning on scheme j on planned GPDP activities and estimated costs. The last two columns show the effects of belonging to a treated GP and having a larger share of citizens preferring more work to be done on scheme j. Controls for estimated cost include total population of the GP, number of villages, total area, distance from district HQ, distance from nearest town and proportion of SC citizens in GP. Controls for count of projects include total population and distance from nearest town. Controls are determined using double select lasso. Schemes in column (1) and (2) include Naljal, Naligali, Pension, Ration, Solarlight, Toilet (Shauchalay), NREGA and Awas. Schemes in column (3) and (4) include Naljal, Naligali, Pension, Ration, Solarlight, Toilet (Shauchalay), NREGA, Ayushman, Education, Hariyali, Healthcare, Kanyavivah, Lokshikayat, RTPS, Scholarship, Udhami and Awas Both District and Scheme effects are controlled for. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

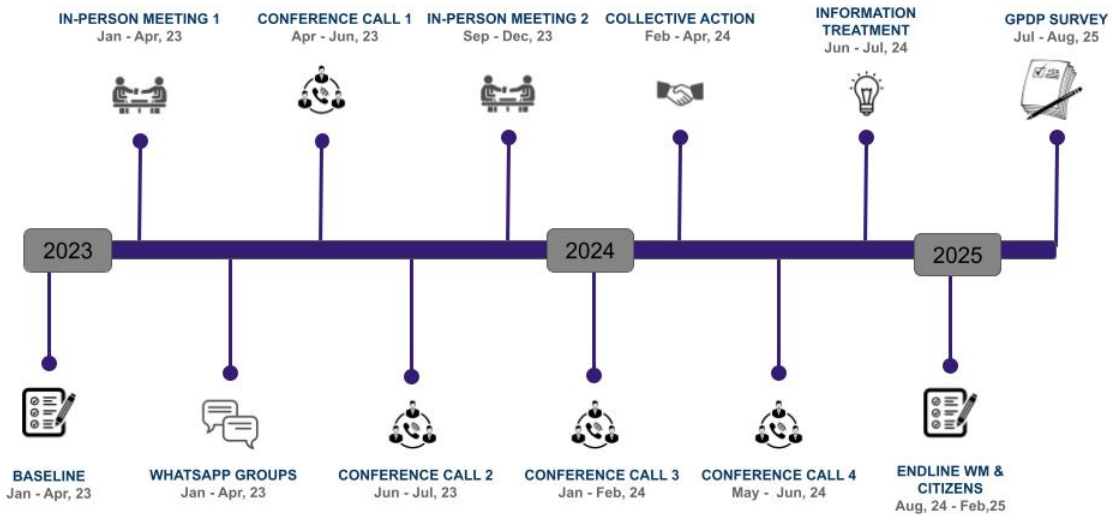
B Main Figures

Figure 1. **Sampling Strategy**



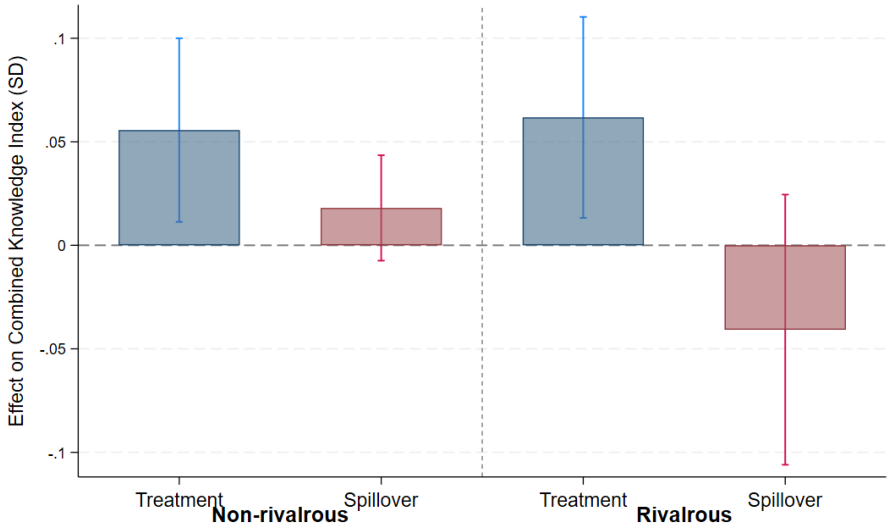
Notes: Figure documents our sampling strategy.

Figure 2. **Timeline**



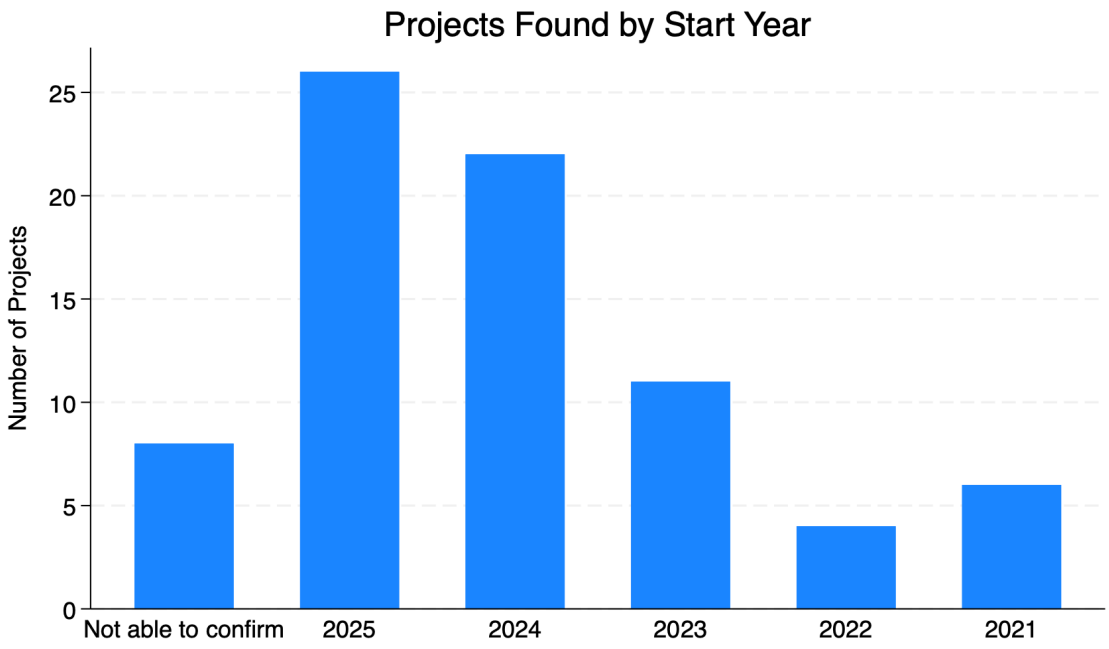
Notes: Figure displays timeline of activities.

Figure 3. **Direct and Spillover Effects for Rivalrous vs Non-Rivalrous Schemes**
Conditional on WM belonging to a group with an above-median number of best practices discussed



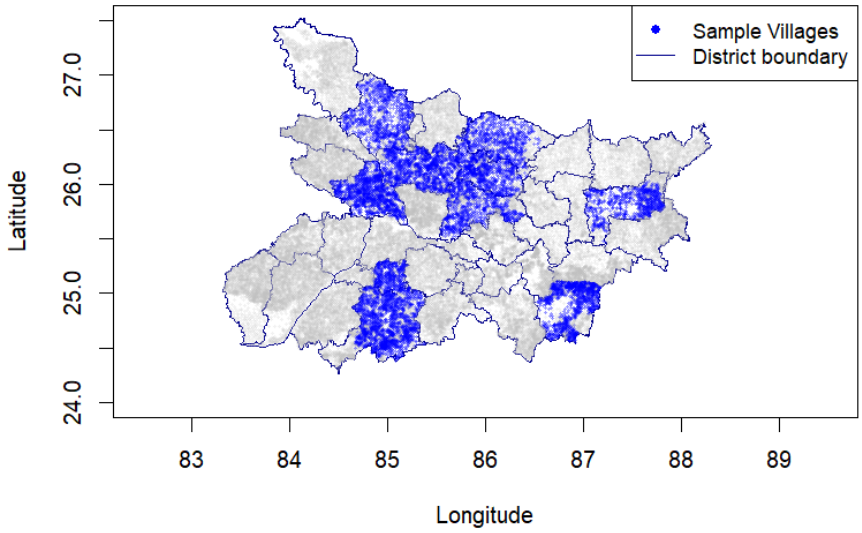
Notes: The figure shows the treatment and spillover effects on knowledge index (combined) for rivalrous and non-rivalrous schemes conditional on the ward member belonging to a group where the number of best practices discussed are above the median number of best practices shared across all groups. Rivalrous 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 NalJal, NaliGali and MGREGA. 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 other local bureaucrats. Controls for both treatment and spillover regressions are determined using double select lasso. The knowledge index is standardised using the control mean.

Figure 4. **When GPDP projects were created (Audit 2025)**

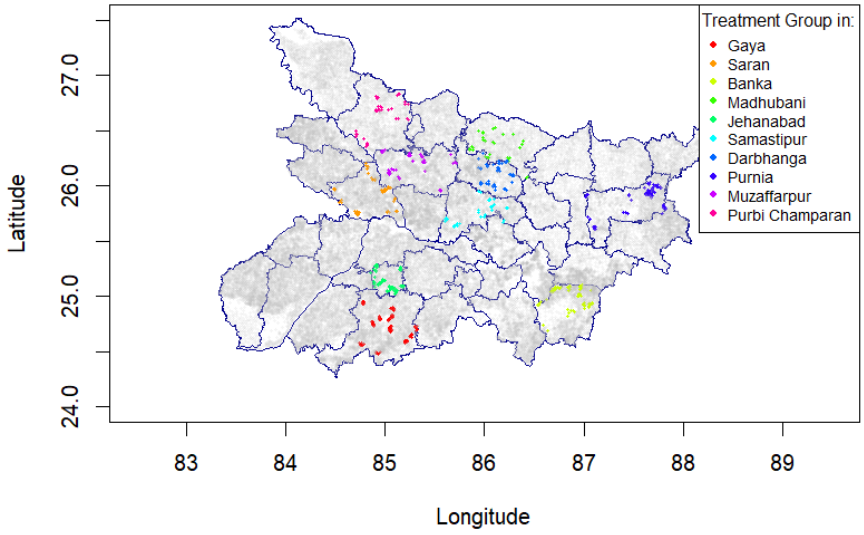


Notes: Figure documents the year in which projects were undertaken.

Figure 5. **Maps of Experiment Area and Sample Treated Groups From Each District**



(a) The above figure marks all villages belonging to the treatment and control GPs in the experiment



(b) The above figure marks all villages belonging to GPs of ward members of a random treatment group from each district included in the experiment

Appendix

C Appendix Tables **48**

D Appendix Figures **73**

E Learning from WhatsApp Groups **75**

F Attrition-Adjusted Estimates **78**

F.1 AIPW - Doubly Robust Estimates 80

F.2 Lee Bounds 81

G Appendix: Indices **82**

G.1 Knowledge 82

G.2 Networks 84

G.3 Confidence 85

G.4 Citizen Assessments 86

C Appendix Tables

Table C1. 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
Darbhanga	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 C2. 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
Darbhanga	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 and (ii) number of wards across treatment and control GPs in our sample.

Table C3. 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	811.842	811.350	810.366	4.947	5.867
	(179.009)	(207.823)	(174.305)	(8.264)	(6.372)
Ward SC Population	181.730	190.070	177.601	11.453	9.246
	(186.308)	(237.125)	(209.928)	(7.967)	(6.990)
Votes Obtained	153.878	151.852	152.711	-1.336	0.649
	(59.254)	(58.742)	(57.573)	(2.212)	(1.904)
Tot. Candidates	4.718	4.722	4.629	-0.010	-0.013
	(1.908)	(1.844)	(1.892)	(0.069)	(0.062)
Age	38.956	38.400	39.280	-0.162	0.119
	(11.354)	(11.369)	(11.851)	(0.389)	(0.360)
SC	0.327	0.333	0.323	0.017	-0.002
	(0.469)	(0.472)	(0.468)	(0.017)	(0.015)
Hindu	0.879	0.889	0.864	0.006	-0.013
	(0.326)	(0.314)	(0.342)	(0.011)	(0.011)
Muslim	0.118	0.107	0.133	-0.007	0.014
	(0.322)	(0.309)	(0.340)	(0.011)	(0.011)
Years of Education	10.219	10.292	10.190	-0.030	-0.038
	(3.956)	(3.837)	(4.024)	(0.138)	(0.126)
Campaigned:	0.827	0.821	0.816	-0.005	0.000
Drains and lanes	(0.378)	(0.384)	(0.388)	(0.013)	(0.012)
Campaigned:	0.547	0.518	0.519	-0.013	-0.026*
Tap water	(0.498)	(0.500)	(0.500)	(0.017)	(0.015)
Campaigned:	0.181	0.200	0.196	0.001	0.005
Pensions	(0.385)	(0.400)	(0.397)	(0.013)	(0.012)
Campaigned:	0.271	0.277	0.289	-0.027*	0.004
Housing	(0.444)	(0.448)	(0.453)	(0.015)	(0.014)
Prev. Experience	0.315	0.312	0.317	-0.001	-0.002
	(0.465)	(0.464)	(0.465)	(0.016)	(0.014)
Prev. Experience	0.103	0.101	0.089	0.002	-0.013
(Family)	(0.303)	(0.301)	(0.284)	(0.011)	(0.009)
Income Source:	0.333	0.366	0.330	0.023	0.007
Agriculture	(0.471)	(0.482)	(0.470)	(0.017)	(0.014)
Received training	0.920	0.926	0.916	0.008	-0.012
	(0.271)	(0.262)	(0.277)	(0.010)	(0.008)
Observations	3,460	2,424	1,835	5,884	5,295

Note: This table displays the balance across Treatment, Control and Spillover samples across administrative and baseline survey data. 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 C4. Balance across Treatment, Control and Spillover Wards (2)

Variable	(1) Control	(2) Treatment	(3) Spillover	(4) T vs C	(5) S vs C
Knowledge: Housing	0.387	0.380	0.395	-0.009	0.007
	(0.191)	(0.183)	(0.194)	(0.006)	(0.006)
Knowledge: Drains and lanes	0.198	0.197	0.207	-0.009	0.002
	(0.216)	(0.210)	(0.221)	(0.008)	(0.007)
Knowledge: Tap water	0.108	0.106	0.095	0.000	-0.007
	(0.166)	(0.149)	(0.156)	(0.012)	(0.009)
Knowledge: Rations (PDS)	0.729	0.703	0.743	0.016	-0.004
	(0.336)	(0.344)	(0.338)	(0.022)	(0.016)
Knowledge: Pensions	0.504	0.523	0.519	0.027	0.009
	(0.249)	(0.271)	(0.249)	(0.017)	(0.012)
Knowledge: Solar lights	0.384	0.386	0.379	-0.017*	-0.005
	(0.266)	(0.276)	(0.269)	(0.010)	(0.008)
Knowledge Index Z Score	0.040	-0.099	0.058	-0.043	0.024
	(0.988)	(0.999)	(1.014)	(0.034)	(0.030)
Knowledge Index PCA Score	0.001	-0.026	0.014	0.007	0.008
	(1.496)	(1.549)	(1.490)	(0.119)	(0.079)
Networks: Block	0.190	0.228	0.206	0.019	0.011
	(0.444)	(0.493)	(0.473)	(0.017)	(0.014)
Networks: Dist.	0.019	0.023	0.023	0.006	0.002
	(0.152)	(0.153)	(0.153)	(0.006)	(0.005)
Networks: State	0.005	0.005	0.005	0.001	0.000
	(0.088)	(0.069)	(0.080)	(0.003)	(0.002)
Networks: All	0.200	0.244	0.220	0.026	0.013
	(0.492)	(0.533)	(0.523)	(0.019)	(0.016)
Interested in Peer	0.956	0.946	0.943	-0.010	-0.009
Learning	(0.206)	(0.227)	(0.233)	(0.007)	(0.007)
Pol. Party Involvement	0.203	0.206	0.218	-0.007	0.012
	(0.403)	(0.405)	(0.413)	(0.014)	(0.013)
WhatsApp	0.805	0.811	0.806	0.002	0.003
	(0.396)	(0.392)	(0.396)	(0.014)	(0.012)
Observations	3,460	2,424	1,835	5,884	5,295

Note: 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. tap water (Nal Jal), housing (PMAY: the main housing scheme), drains/lanes implementation (Naligali Yojana), solar lights scheme, tap water 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. All regressions have district FE. Errors are clustered at the GP level. P values: * 0.1 ** 0.05 *** 0.01.

Table C5. **Distribution of Procedural Knowledge Shares for Each Scheme**

	Mean	**SD**	**P10**	**P25**	**Median**	**P75**	**P90**
Accounts	.5090239	.290709	0	.3333333	.5	.6666667	.8333333
PMAY	.3866978	.189293	.2	.2	.4	.6	.6
Nali Gali	.1995238	.2151904	0	0	.1111111	.3333333	.4444444
Nal Jal	.1044651	.1611631	0	0	0	.2	.4
PDS	.7277076	.3379836	0	.5	.75	1	1
Pension	.5113894	.2531208	.1428571	.4285714	.5714286	.7142857	.7142857
Solar Lighting	.3833333	.2699095	0	.2	.4	.6	.8
All Schemes (Mean)	.3960431	.1635083	.1755102	.2805555	.4	.5146825	.6083333

Notes: Each entry reports the share of procedural steps known by ward members for a given scheme. Shares are normalized by the maximum number of steps observed for that scheme.

Table C6. **Learning Heterogeneity with Group Baseline Education, Knowledge, Experience, Networks**

	(1) **Combined Index (std)**	(2) **Combined Index (std)**	(3) **Combined Index (std)**	(4) **Combined Index (std)**
Treated Ward	0.120***	0.132***	0.169***	0.134***
	(0.039)	(0.039)	(0.041)	(0.039)
Above Median Education (of group)	0.013			
	(0.049)			
Above Median Knowledge (of group)		-0.010		
		(0.048)		
Above Median Experience (of group)			-0.083*	
			(0.048)	
Above Median Networks beyond GP (of group)				-0.014
				(0.048)
Observations	4415	4415	4415	4415
WM Controls	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0

Notes: Each column shows the effect of treatment and of belonging to a group with above median levels of a peer characteristic (compared to other treated groups). Column 1: peer education, Column 2: peer baseline knowledge, Column 3: peer experience (whether elected before), Column 4: peer networks. 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 recieved training and dummies that control for access to local bureaucrats and connectivity through phone. The outcome index is standardized using the control group mean and standard deviation. Regressions control for both district and scheme fixed effects. Standard errors are clustered at the UGP level and are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C7. **Heterogeneous Effects of Rivalrous Schemes with Above Median number of Best Practices discussed.**

	(1)	(2)	(3)	(4)	(5)
	Formal Knowledge Index (std)	**Tacit Knowledge Index (std)**	**Procedural Index (std)**	**Best Practices Index (std)**	**Combined Index (std)**
	Index for each WM at the Scheme level				
Treatment Ward	-0.0352	0.0127	0.0097	-0.0055	-0.0073
	(0.0308)	(0.0304)	(0.0303)	(0.0217)	(0.0226)
WM in above median sol. meeting	0.0865***	0.0226	0.0183	0.0509**	0.0556**
	(0.0297)	(0.0333)	(0.0339)	(0.0240)	(0.0226)
WM in above median sol. meeting × Rivalrous scheme	0.0058	0.0342	0.0896	0.0646**	0.0618**
	(0.0330)	(0.0360)	(0.0653)	(0.0286)	(0.0247)
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 schemes that are categorised as rivalrous compared to schemes that are categorised as non-rivalrous on learnings for those ward members who were in groups where above median best practices/solutions were discussed. We define rivalrous schemes as those schemes 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 NalJal, NaliGali and MGREGA. 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 recieved 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 C8. **Spillover Heterogeneous Effects of Rivalrous Schemes with Above Median Number of Best Practices Discussed.**

	(1) Formal Knowledge Index (std)	(2) Tacit Knowledge Index (std)	(3) Procedural Index (std)	(4) Best Practices Index (std)	(5) Combined Index (std)
	Index for each WM at the Scheme level				
Spillover Ward	0.0050	0.0183	-0.0519	0.0464*	0.0299
	(0.0380)	(0.0380)	(0.0511)	(0.0273)	(0.0284)
Count of WM in above median sol. meeting in GP	0.0173	0.0157	0.0522**	0.0074	0.0180
	(0.0174)	(0.0180)	(0.0255)	(0.0126)	(0.0130)
Count of WM in above median sol. meeting in GP X Rivalrous scheme	-0.0119	-0.0652	0.1009	-0.0524	-0.0408
	(0.0497)	(0.0498)	(0.1285)	(0.0366)	(0.0333)
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 schemes that are categorised as rivalrous compared to schemes that are categorised as non-rivalrous on learnings for those ward members who were in groups where above median best practices/solutions were discussed. We define rivalrous schemes as those schemes 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 NalJal, NaliGali and MGREGA. 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 recieved 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 C9. **Heterogeneous Effects of Rivalrous Schemes**

	(1)	(2)	(3)	(4)	(5)
	Formal Knowledge Index (std)	**Tacit Knowledge Index (std)**	**Procedural Index (std)**	**Best Practices Index (std)**	**Combined Index (std)**
	Index for each WM at the Scheme level				
Treatment Ward	0.0301	0.0429*	0.0213	0.0335*	0.0399**
	(0.0233)	(0.0232)	(0.0205)	(0.0177)	(0.0182)
Treatment Ward × Rivalrous scheme	-0.0036	-0.0190	0.0799	0.0341	0.0253
	(0.0288)	(0.0318)	(0.0609)	(0.0264)	(0.0226)
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 schemes that are categorised as rivalrous compared to schemes that are categorised as non-rivalrous on learnings. We define rivalrous schemes as those schemes 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 NalJal, NaliGali and MGREGA. 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 recieved 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 C10. **Spillover Heterogeneous Effects of Rivalrous Schemes.**

	(1) **Formal Knowledge Index (std)**	(2) **Tacit Knowledge Index (std)**	(3) **Procedural Index (std)**	(4) **Best Practices Index (std)**	(5) **Combined Index (std)**
	Index for each WM at the Scheme level				
Spillover Ward	0.0219	0.0402	0.0162	0.0698***	0.0679***
	(0.0257)	(0.0254)	(0.0289)	(0.0198)	(0.0201)
Spillover Ward X Rivalrous scheme	0.0416	-0.0102	0.1384	-0.0532*	-0.0369
	(0.0319)	(0.0350)	(0.0860)	(0.0298)	(0.0249)
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 schemes that are categorised as rivalrous compared to schemes that are categorised as non-rivalrous on learnings. We define rivalrous schemes as those schemes 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 NalJal, NaliGali and MGREGA. 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 recieved 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 C11. **Heterogeneity by Above Median Discussion Time: Treatment and Spillover Effects**

	Index for each WM at the Scheme level				
	(1)	(2)	(3)	(4)	(5)
	Formal Knowledge Index (std)	**Tacit Knowledge Index (std)**	**Procedural Index (std)**	**Best Practices Index (std)**	**Combined Index (std)**
Panel A: Treatment — Above Median Discussion Time					
Treatment Ward	0.0139	0.0173	0.0232	0.0363*	0.0368*
	(0.0254)	(0.0249)	(0.0242)	(0.0191)	(0.0192)
Above Median Discussion Time	0.0292	0.0376	0.0188	0.0165	0.0255
	(0.0240)	(0.0267)	(0.0291)	(0.0195)	(0.0172)
Observations	17636	14312	10366	26454	33085
Panel B: Spillover — Above Median Discussion Time					
Spillover Ward	0.0253	0.0075	-0.0066	0.0385*	0.0339
	(0.0317)	(0.0303)	(0.0407)	(0.0229)	(0.0235)
Count of WM Above Median Discussion Time in GP	0.0059	0.0247	0.0368	0.0115	0.0161
	(0.0178)	(0.0169)	(0.0254)	(0.0129)	(0.0128)
Observations	16184	13096	7718	24276	30311
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: Panel A examines treatment heterogeneity by discussion time. A ward member is classified as having above median discussion time if their meeting's discussion time exceeds the median across all meetings. Panel B examines spillover heterogeneity by the count of ward members in the GP who participated in meetings with above median discussion time. The controls for panel A include baseline knowledge, confidence, education, age and dummies that control for access to local bureaucrats and connectivity through phone. Panel A also accounts for district fixed effects. The controls for Panel B include all of the above controls as well as baseline networks, caste, controls for political and bureaucratic affiliation, past experience, employment status, interest in study participation, if ward member recieved training and additional dummies that control for access other local bureaucrats. Panel B controls for both district and scheme 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 C12. **Treatment Effects on Relationships and Conflict with Local Bureaucrats & Politicians**

	WM Discuss Work Difficulty With:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Rozgar Sevak	**Panchayat Secretary**	**GP Head**	**Block Development Officer**	**Conflict BPRO**	**Conflict BDO**	**Conflict GP Head**
Treated Ward	0.0015	-0.0028	-0.0920***	-0.0163	0.0028	0.0069**	0.0343***
	(0.0046)	(0.0036)	(0.0148)	(0.0106)	(0.0026)	(0.0035)	(0.0102)
Observations	4663	4663	4663	4663	4663	4663	4659
WM Controls	No	No	No	No	No	No	No
Ward Level Controls	No	No	No	No	No	No	No
Control Mean	.021	.017	.571	.148	.006	.01	.114

Notes: The above table reports the effect of treatment on conflicts and relationships with local bureaucrats and politicans. Each regression controls for district fixed effects. The table reports results 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 C13. **Percentage of Surveyed Citizens Who Perceive Ward Member as the Contact for Scheme-Related Help**

	(1)	(2)	(3)	(4)	(5)
	Nal Jal	**Education**	**Ration**	**NREGA**	**PMAY**
Percent of Citizens	64.17	14.47	19.07	28.76	33.35
Observations	3581	9699	4766	4764	4929

Entries report the percentage of all surveyed citizens who identify the Ward Member as their primary help contact for the specified scheme.

Table C14. **Ward Members' belief on schemes where they are primarily responsible**

Scheme	Percent of Cases
Nali Gali	63.26%
Nal jal	54.39%
PMAY	21.29%
Don't know	18.03%
Shauchalay	16.34%
Pension	15.61%
Solar light	12.98%
Sat Nischay	10.58%
MNREGA	9.03%
PDS	8.72%
Monitoring development work	8.55%
Conflict resolution support	1.19%
Other schemes	0.92%

Entries report the percentage of all surveyed ward members who identify the ward member as primary person responsible for the specified scheme.

Table C15. **Effects of Above Median Discussion Time on GPDP Planned Activities and Estimated Costs**

	Projects in each GP at the Scheme Level			
	(1) **Total Projects (Count)**	(2) **Total Projects (Count)**	(3) **Estimated Cost (Absolute)**	(4) **Estimated Cost (Absolute)**
Treated GP	0.055	0.054	17170.303	16495.065
	(0.057)	(0.062)	(16983.898)	(18002.759)
Treat × WMs in Above Median Time	0.036	0.036	17149.355*	17281.466*
	(0.032)	(0.033)	(9640.102)	(10332.153)
Observations	19422	19422	19422	19422
GP-Level Controls	No	Yes	No	Yes
Control Mean	1.838	1.838	702093.813	702093.813

Notes: This table reports the effects of treatment heterogeneity by above-median discussion time on GP-level planned GPDP projects and estimated costs at the GP × scheme level. Ward members are classified as having above-median discussion time if the total time spent discussing schemes in their meetings exceeds the median across all meetings. GP-level controls for count of projects include total population, number of villages, total area, distance from district HQ, distance from nearest town and proportion of SC citizens in the GP and controls for estimated cost include include total population and distance from nearest town. Controls are determined by double select lasso. Regressions control for district and scheme fixed effects. Schemes include includes schemes Naljal, Naligali, NREGA, Solarlights, Toilet (Shauchalya), LSBA, Pension and Ration. Robust standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C16. **Summary of Projects by Scheme**

	Share Audited (%)	**Share Found (%)**
NREGS	45.0	20.8
Nal Jal	2.7	0.7
NaliGali	34.2	15.4
Solar Street Lights	18.1	14.8
Total Projects	100.0	51.7

Source: GPDP Audit Survey Column (1) of the above table gives us the share of projects audited under each scheme in the survey. Column (2) details the share of projects found out of the total projects audited.

Table C17. **Project Completion Status by Scheme**

Year of Completion	NaliGali (%)	NREGS (%)	Solar Street Lights (%)	Nal Jal (%)
Not able to confirm	22.2	77.8	0.0	0.0
2025	44.4	11.1	44.4	0.0
2024	10.5	52.6	36.8	0.0
2023	28.6	71.4	0.0	0.0
2022	100.0	0.0	0.0	0.0
2021	57.1	28.6	0.0	14.3

Source: GPDP Audit Survey. There are a total of 77 located projects, out of which 16 were still ongoing at the time of the survey. The table is determined using the 61 completed projects.

Table C18. **Ward Member Involvement by Scheme**

	Ward Member Role (%)	**Total Projects**
NREGS	11.5	26
Nal Jal	0.0	1
NaliGali	47.4	19
Solar Street Lights	66.7	15
Total	36.1	61

Source: GPDP Audit Survey. 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. The Total row reports the share across all schemes. Column (2) gives the total number of completed projects that were found for each scheme.

Table C19. **Project Completion: Main Responsibility**

Person Responsible	NaliGali (%)	NREGS (%)	Solar Street Lights (%)	Nal Jal (%)
Ward member	5.3	3.8	60.0	0.0
Mukhiya	78.9	61.5	13.3	0.0
Panchayat Sachiv	5.3	3.8	6.7	0.0
Contractor/Dealer	0.0	3.8	0.0	0.0
Dont know/ dont 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

The table shows, for each scheme, the share of projects attributed to different local actors. 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.

Table C20. **Treatment Effects on NREGA Work Days**

	(1) **Total Person Days**	(2) **Total HH Worked**	(3) **SC Person Days**	(4) **Women Person Days**
Panel A: Year 2024–2025				
Treated GP	-196.631	-1.199	-109.701	-230.980
	(642.702)	(10.407)	(213.083)	(372.339)
Observations	2171	2171	2171	2171
Control Mean	28138.932	590.689	5810.186	16009.261
Panel B: Year 2023-2024				
Treated GP	-737.9262	-3.9817	-100.1954	-537.0048
	(597.8979)	(10.3373)	(189.4186)	(345.6842)
Observations	2156	2156	2156	2156
GP Controls	Yes	Yes	Yes	Yes
Pre-period Controls	Yes	Yes	Yes	Yes
Control Mean	25834.115	564.997	5229.82	14542.101

Notes: The above table shows the effect of Treatment on NREGA outcomes. Column (1), (3) and (4) show effects of treatment on person days in total, for SC and women respectively. Column (2) shows effect of treatment on total households worked. Panel A shows estimates for period 2024–2025 and Panel B for 2023-2024. 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 C21. **Balance Table: Baseline Characteristics by Endline Survey Status**

Variable	(1) Found	(2) Not Found	(3) Found vs Not Found
Ward population	812.984	804.135	9.528
	(190.493)	(175.672)	(6.022)
pop_sc	186.029	167.924	18.735***
	(214.178)	(184.321)	(6.612)
Votes Obtained	153.801	148.979	4.860**
	(59.092)	(57.043)	(1.921)
Tot. Candidates	4.695	4.761	-0.050
	(1.883)	(1.879)	(0.061)
Age	38.897	38.133	0.757**
	(11.380)	(11.355)	(0.359)
SC	0.332	0.295	0.038***
	(0.471)	(0.456)	(0.014)
Hindu	0.881	0.867	0.014
	(0.323)	(0.340)	(0.010)
Muslim	0.116	0.128	-0.012
	(0.320)	(0.335)	(0.010)
Years of Education	10.174	10.531	-0.369***
	(3.886)	(4.154)	(0.128)
Nali -Gali	0.824	0.813	0.009
	(0.381)	(0.390)	(0.012)
Nal Jal	0.525	0.559	-0.035**
	(0.499)	(0.497)	(0.015)
Pension; Old age, CM	0.193	0.177	0.015
pension	(0.394)	(0.382)	(0.012)
Indira Awas	0.286	0.238	0.049***
	(0.452)	(0.426)	(0.013)
Prev. Experience	0.321	0.285	0.038***
	(0.467)	(0.452)	(0.014)
Ever WM before, from	0.100	0.090	0.011
family	(0.301)	(0.286)	(0.009)
Income Source:	0.343	0.339	0.005
Agriculture	(0.475)	(0.473)	(0.015)
Received training	0.924	0.909	0.015
	(0.266)	(0.287)	(0.009)
Treated Ward	0.315	0.326	-0.012
	(0.464)	(0.469)	(0.014)
Control Ward	0.436	0.495	-0.059***
	(0.496)	(0.500)	(0.015)
Spillover Ward	0.249	0.179	0.071***
	(0.433)	(0.383)	(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 with standard errors clustered at the GP level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C22. **Balance Table: Baseline Characteristics by Endline Survey Status (2)**

Variable	(1) Found	(2) Not Found	(3) Found vs Not Found
Knowledge:	0.388	0.380	0.008
Housing	(0.189)	(0.188)	(0.006)
Knowledge:	0.203	0.184	0.019***
Drains/Lanes	(0.215)	(0.216)	(0.007)
Knowledge: Tap	0.108	0.090	0.015*
Water	(0.163)	(0.154)	(0.009)
Knowledge: PDS	0.736	0.690	0.047***
	(0.335)	(0.348)	(0.017)
Knowledge:	0.519	0.478	0.039***
Pension	(0.252)	(0.255)	(0.012)
Knowledge:	0.387	0.364	0.022**
Solar Lights	(0.270)	(0.268)	(0.009)
Scheme steps Knowledge	0.000		0.000
Index z-score	(1.000)	()	(0.000)
Knowledge Index	0.058	-0.265	0.310***
(PCA)	(1.492)	(1.525)	(0.086)
Baseline block peer	0.216	0.157	0.060***
network	(0.478)	(0.405)	(0.013)
Baseline district peer	0.023	0.015	0.007*
network	(0.157)	(0.129)	(0.004)
Networks: State	0.006	0.000	0.006***
	(0.088)	(0.000)	(0.001)
Networks: All	0.245	0.172	0.074***
	(0.540)	(0.440)	(0.014)
Interested in Peer	0.952	0.936	0.015**
Learning	(0.213)	(0.245)	(0.007)
Involvement in the	0.214	0.181	0.034***
political party	(0.410)	(0.385)	(0.012)
WhatsApp	0.809	0.796	0.014
	(0.393)	(0.403)	(0.012)
Treated Ward	0.315	0.326	-0.012
	(0.464)	(0.469)	(0.014)
Control Ward	0.436	0.495	-0.059***
	(0.496)	(0.500)	(0.015)
Spillover Ward	0.249	0.179	0.071***
	(0.433)	(0.383)	(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 with standard errors clustered at the GP level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C23. **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	813.108	811.601	-0.601	-2.108
	(180.153)	(214.507)	(175.610)	(7.141)	(6.811)
pop_sc	184.075	193.647	179.975	9.573	-4.100
	(185.454)	(248.155)	(214.104)	(7.998)	(7.780)
Votes Obtained	154.600	152.674	153.789	-1.926	-0.812
	(59.388)	(59.660)	(57.844)	(1.933)	(1.978)
Tot. Candidates	4.721	4.728	4.607	0.006	-0.115*
	(1.898)	(1.845)	(1.903)	(0.062)	(0.067)
Age	38.967	38.536	39.231	-0.432	0.263
	(11.313)	(11.218)	(11.695)	(0.342)	(0.386)
SC	0.330	0.344	0.321	0.014	-0.009
	(0.470)	(0.475)	(0.467)	(0.014)	(0.016)
Hindu	0.880	0.895	0.866	0.015	-0.015
	(0.324)	(0.306)	(0.341)	(0.011)	(0.012)
Muslim	0.117	0.102	0.132	-0.016	0.015
	(0.322)	(0.302)	(0.338)	(0.010)	(0.012)
Years of Education	10.182	10.204	10.122	0.022	-0.059
	(3.889)	(3.801)	(3.987)	(0.118)	(0.131)
Nali -Gali	0.835	0.819	0.813	-0.015	-0.022*
	(0.372)	(0.385)	(0.390)	(0.012)	(0.013)
Nal Jal	0.549	0.505	0.510	-0.044***	-0.039**
	(0.498)	(0.500)	(0.500)	(0.015)	(0.016)
Pension; Old age, CM	0.181	0.202	0.201	0.021*	0.020
pension	(0.385)	(0.402)	(0.401)	(0.012)	(0.013)
Indira Awas	0.281	0.282	0.298	0.002	0.017
	(0.449)	(0.450)	(0.458)	(0.014)	(0.015)
Prev. Experience	0.319	0.325	0.318	0.006	-0.001
	(0.466)	(0.469)	(0.466)	(0.014)	(0.015)
Ever WM before, from	0.107	0.103	0.087	-0.004	-0.019**
family	(0.309)	(0.304)	(0.282)	(0.009)	(0.009)
Income Source:	0.337	0.366	0.326	0.028*	-0.011
Agriculture	(0.473)	(0.482)	(0.469)	(0.015)	(0.015)
Received training	0.923	0.927	0.920	0.004	-0.003
	(0.267)	(0.260)	(0.271)	(0.008)	(0.009)
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. 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 val-ues: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C24. **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
Knowledge:	0.392	0.379	0.394	-0.012**	0.000
Housing	(0.193)	(0.182)	(0.193)	(0.006)	(0.006)
Knowledge:	0.199	0.202	0.209	0.004	0.003
Drains/Lanes	(0.216)	(0.210)	(0.220)	(0.007)	(0.008)
Knowledge: Tap	0.112	0.108	0.097	0.006	-0.008
Water	(0.168)	(0.149)	(0.157)	(0.012)	(0.009)
Knowledge: PDS	0.739	0.717	0.741	0.000	-0.003
	(0.330)	(0.342)	(0.344)	(0.020)	(0.017)
Knowledge:	0.514	0.532	0.518	0.024	0.002
Pension	(0.246)	(0.270)	(0.253)	(0.015)	(0.013)
Knowledge:	0.390	0.391	0.376	0.003	-0.014
Solar Lights	(0.265)	(0.276)	(0.271)	(0.009)	(0.009)
Scheme steps Knowledge	-0.016	0.004	0.022	0.019	0.049
Index z-score	(0.975)	(1.007)	(1.033)	(0.030)	(0.033)
Knowledge Index	0.077	0.050	0.021	0.069	-0.030
(PCA)	(1.474)	(1.551)	(1.496)	(0.116)	(0.084)
Baseline block peer	0.203	0.236	0.213	0.035**	0.001
network	(0.457)	(0.500)	(0.485)	(0.015)	(0.015)
Baseline district peer	0.021	0.024	0.024	0.003	0.001
network	(0.158)	(0.156)	(0.158)	(0.005)	(0.005)
Networks: State	0.006	0.006	0.006	-0.001	-0.001
	(0.098)	(0.076)	(0.085)	(0.003)	(0.003)
Networks: All	0.230	0.266	0.243	0.037**	0.001
	(0.525)	(0.551)	(0.551)	(0.016)	(0.018)
Interested in Peer	0.958	0.950	0.945	-0.007	-0.009
Learning	(0.201)	(0.218)	(0.228)	(0.006)	(0.007)
Involvement in the	0.210	0.211	0.222	0.001	0.009
political party	(0.408)	(0.408)	(0.416)	(0.012)	(0.014)
WhatsApp	0.809	0.815	0.803	0.008	0.001
	(0.393)	(0.389)	(0.398)	(0.012)	(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. 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 val-ues: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C25. **Learning Heterogeneity: Scheme-Level RF Residualized**

	Index for each WM at the Scheme level				
	(1)	(2)	(3)	(4)	(5)
	Formal Knowledge Index (std)	**Tacit Knowledge Index (std)**	**Procedural Index (std)**	**Best Practices Index (std)**	**Combined Index (std)**
Treated Ward	0.022	0.027	0.035	0.038*	0.031
	(0.028)	(0.030)	(0.034)	(0.021)	(0.022)
Above Median Predicted (Scheme RF)	0.046	0.014	0.046	0.033	0.053**
	(0.031)	(0.034)	(0.038)	(0.023)	(0.024)
Observations	12954	9697	5833	21590	28073
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	.001

Notes: Scheme-level RF with district and scheme FE partialled out (Frisch–Waugh). 1,648 group-by-scheme observations. RF OOB $R^2 = 0.006$ on residualized outcomes. Above-median defined within scheme. Controls: gender, age, caste, education, networks, baseline knowledge. SE clustered at GP level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C26. **Learning Heterogeneity: Scheme-Level LASSO**

	Index for each WM at the Scheme level				
	(1)	(2)	(3)	(4)	(5)
	Formal Knowledge Index (std)	**Tacit Knowledge Index (std)**	**Procedural Index (std)**	**Best Practices Index (std)**	**Combined Index (std)**
Treated Ward	0.006	0.013	0.009	0.050**	0.038*
	(0.028)	(0.030)	(0.034)	(0.022)	(0.023)
Above Median Predicted (LASSO)	0.076**	0.042	0.097***	0.009	0.038
	(0.033)	(0.034)	(0.037)	(0.025)	(0.025)
Observations	12954	9697	5833	21590	28073
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	.001

Notes: Scheme-level LASSO with cross-validation. District and scheme FE partialled out. 1,648 group-by-scheme observations. LASSO CV $R^2 = 0.004$ on residualized outcomes. Above-median defined within scheme. Controls: gender, age, caste, education, networks, baseline knowledge. SE clustered at GP level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C27. **Impact of Treatment on Outcomes - No Controls**

	(1) Combined Knowledge Index (std)	(2) Combined Knowledge Index (std)	(3) Confidence Index (std)	(4) Networks Index (std)	(5) Total Activities	(6) Estimated Cost
Treatment Ward	0.0960***		0.0901***	0.1716***		
	(0.0311)		(0.0319)	(0.0341)		
Spillover Ward		0.0960***				
		(0.0360)				
Treated GP					0.7665**	231753.3067***
					(0.3217)	(82939.1257)
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	14.489	5002000

Notes: All indices are standardized using the control mean. The combined knowledge index takes the average of all standardized indices and is standardized using the control mean. Confidence index is created by asking WMs about the number of schemes they are confident about. Networks Index is created by taking the average of different networks at block, district, and GP level. Columns 5 and 6 report the effect of treatment on planned GPDP activities and costs. Standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C28. **Impact of Treatment on Outcomes - SE cluster at WG level**

	(1) Combined Knowledge Index (std)	(2) Confidence Index (std)	(3) Networks Index (std)
Treatment Ward	0.1179***	0.1016***	0.1588***
	(0.0296)	(0.0328)	(0.0364)
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

All indices are standardized using the control mean. The combined knowledge index takes the average of all standardized indices and is standardized using the control mean. Confidence index is created by asking WM about no. of schemes they are confident about. Networks Index is created by taking the average of different networks at block, district, GP level. Standard errors are given in parantheses $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table C29. **Learning Heterogeneity with Above Median Best Practices - Pure Exposure**

	Index for each WM at the Scheme level				
	(1)	(2)	(3)	(4)	(5)
	Formal Knowledge Index (std)	**Tacit Knowledge Index (std)**	**Procedural Index (std)**	**Best Practices Index (std)**	**Combined Index (std)**
Treated Ward	-0.013	0.031	0.014	0.018	0.018
	(0.029)	(0.029)	(0.028)	(0.020)	(0.021)
Above Median Best Practices	0.062**	0.010	0.029	0.043**	0.049**
	(0.027)	(0.030)	(0.032)	(0.021)	(0.020)
Observations	17636	14312	10366	26454	33085
WM Controls	Yes	Yes	Yes	Yes	Yes
Ward-Level Controls	Yes	Yes	Yes	Yes	Yes
Control Mean	0	0	0	0	0

Notes: The above table shows heterogeneity of learnings by meeting discussions. A ward member participated in meetings with above median meeting practices if the total number of best practices discussed in their meeting is above the median number of total number of best practices discussed across all meetings. Solutions here are pure exposure, i.e., the solutions a ward member is exposed to is determined using leaving own contributed solutions/best practices out. 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 recieved training and dummies that control for access to local bureaucrats and connectivity through phone. 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 C30. **Effects of Treated Wards on Citizen Reports of Public Goods and Welfare Programs**

	(1) Naljal (Std)	(2) Naligali (Std)	(3) Solar Lights (Std)	(4) LSBA (Std)	(5) Combined Index (Std)	
Panel A: Public Goods						
Treated Wards	0.060*	0.015	-0.017	-0.054*	-0.000	
	(0.033)	(0.032)	(0.035)	(0.033)	(0.024)	
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)	**Ration Card (Std)**	**Pension (Std)**	**Shauchalaya (Std)**	**PMAY (Std)**	**Combined Index (Std)**
Panel B: Welfare Programs						
Treated Wards	-0.011	0.044	0.017	-0.022	0.025	0.019
	(0.032)	(0.033)	(0.029)	(0.032)	(0.032)	(0.023)
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: Panel A reports treatment effects on citizen outcomes/availament of public good schemes. Panel B reports treatment effects on citizen outcomes/availment of welfare programs. All outcomes are standardized using the control group mean and standard deviation. Regressions are run with district fixed effects and no controls. Determination of controls using double select lasso showed low predictive power for all pre-defined variables that were tested with lasso. Standard errors are clustered at the UGP level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C31. **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
Panel A: Self-Dealing						
Treated GP	0.0002	0.0003				
	(0.0002)	(0.0003)				
Treated Ward			0.0024	-0.0023	-3.0197	-1.5478
			(0.0078)	(0.0068)	(3.1196)	(1.7847)
Observations	1506	1506	5551	5551	887	906
Controls	No	No	Ward Controls	Ward Controls	Ward Controls	Ward Controls
Cluster	Robust	Robust	UGP	UGP	UGP	UGP
Control Mean	.003	.003	.079	.057	34.867	16.075
	NREGA	**Ration Card**	**Pension**	**Shauchalaya**	**PMAY**	**Combined Index (Std)**
Panel B: Citizen Reports of Bribe Taken						
Treated Wards	0.003	-0.017*	0.007	0.018	0.037**	0.037
	(0.011)	(0.010)	(0.011)	(0.019)	(0.016)	(0.034)
Observations	891	823	1203	895	855	3650
Controls	No	No	No	No	No	No
Cluster	Ward	Ward	Ward	Ward	Ward	Ward
Control Mean	.022	.031	.037	.08	.038	0

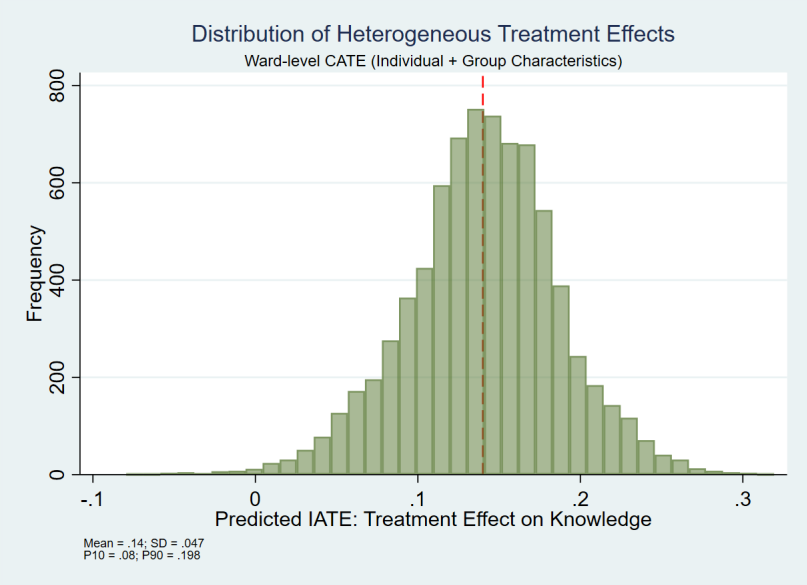
Notes: Panel A presents treatment effects on self-dealing measures. Columns 1–2 show effects on the share of NREGA days worked by ward members within their GP for 2023–2025 and 2024–2025 respectively, with GP-level controls and robust standard errors. Columns 3–4 show effects on a binary indicator for having worked at all, and Columns 5–6 show effects on total day counts, both with ward-level controls and standard errors clustered at the UGP level. Panel B reports treatment effects on citizen reports of bribes taken by ward members for various schemes, with ward-level controls and standard errors clustered at the Ward level. 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 C32. **Effect of Treatment on Within-Group Knowledge Variance**

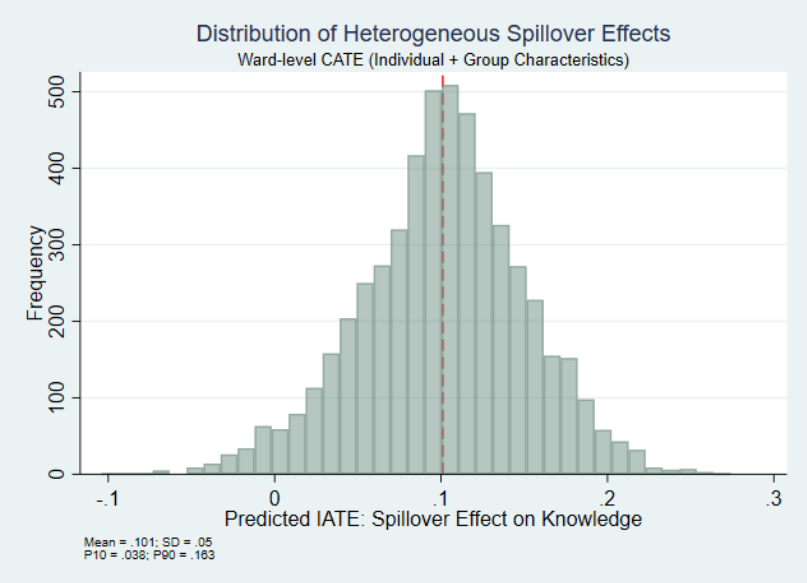
	(1) **Learning Index (Variance)**	(2) **Learning Index (Variance)**	(3) **Knowledge Index (EL) (Variance)**	(4) **Knowledge Index (EL) (Variance)**
Treatment Ward	0.142***	0.141***	0.0634	0.0579
	(0.0440)	(0.0447)	(0.0402)	(0.0410)
Baseline Knowledge Variance	-0.0148	-0.0144	0.0204	0.0220
	(0.0550)	(0.0550)	(0.0499)	(0.0511)
Observations	498	498	498	498
Controls	No	Yes	No	Yes

All specifications include district fixed effects. Controls include: SC Reserved, ST Reserved, EBC Reserved, Age, Woman, Education, Average GP, Block and District Networks.
Robust standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$.

D Appendix Figures

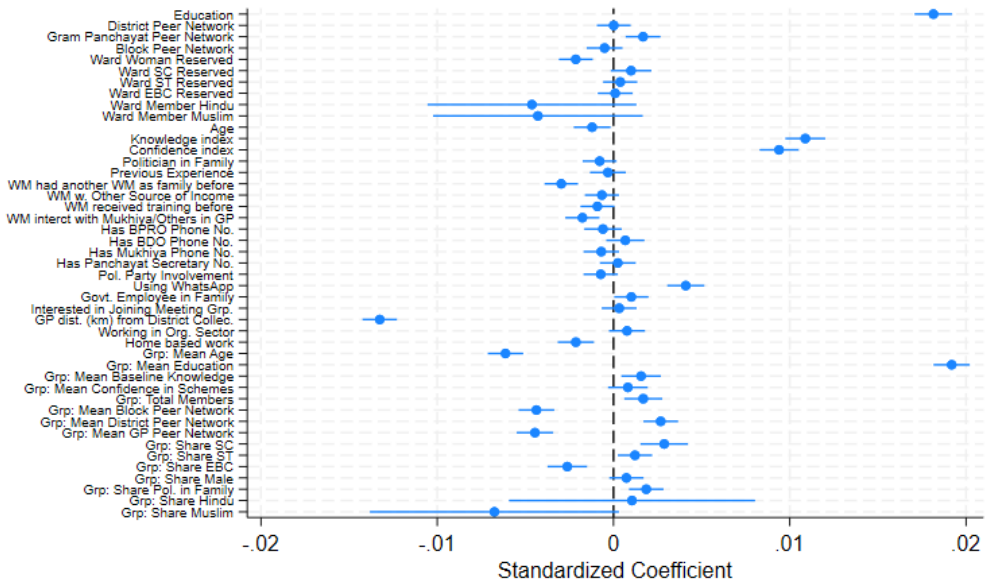


(a) Distribution of Predicted IATE (controlling for Individual and Group Characteristics)

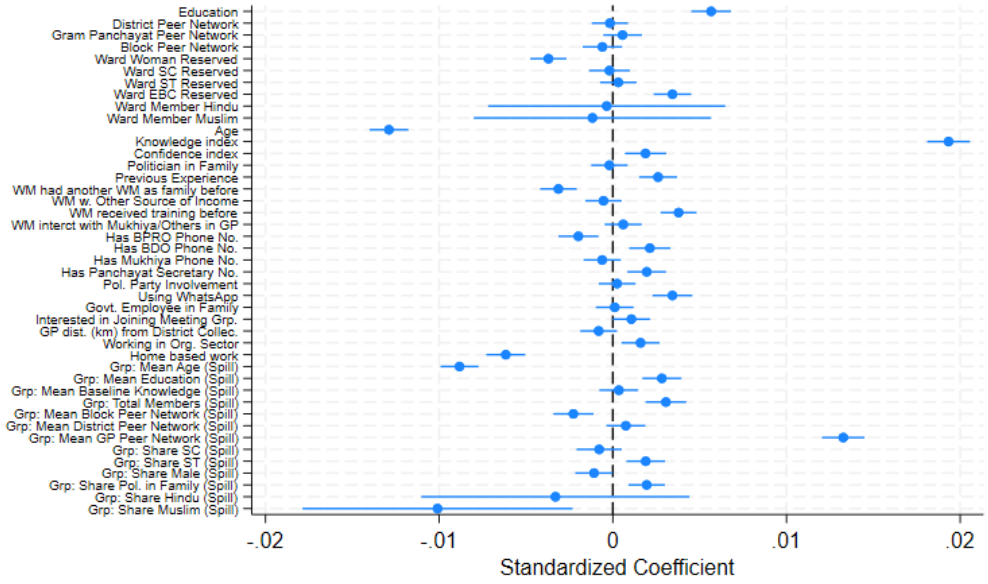


(b) Distribution of Predicted Conditional Spillover Effects (controlling for Individual and Group Characteristics)

Figure D1. **Distribution of Heterogeneous Treatment and Spillover Effects for Combined Learnings 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

Figure D2. **Heterogeneous Treatment and Spillover Effects for Combined Learnings Index (Group variables for Spillover effects are measured by taking mean of group characteristics for treated ward members belonging to the GP)**

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 LSBA (mean 6.2 messages per group), Nal Jal (4.9), and MGNREGA (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 E1), 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 E2), 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).

Across all four specifications, the combined knowledge index is positively associated with WhatsApp scheme discussion, though the magnitude and precision

vary with the level of aggregation. The WM-level specifications – which pool discussion across all schemes within a group – yield the strongest and most precisely estimated effects (combined index: 0.096 SD in the binary specification, 0.041 SD in the continuous specification).

Table E1. **Learning Heterogeneity by Above-Median Scheme Discussion**

	(1) **Formal Knowledge Index (std)**	(2) **Tacit Knowledge Index (std)**	(3) **Procedural Index (std)**	(4) **Best Practices Index (std)**	(5) **Combined Index (std)**
Treatment Ward	0.027	0.022	0.075**	0.043**	0.042**
	(0.026)	(0.027)	(0.030)	(0.018)	(0.019)
Above Median Scheme Texts	0.030	0.006	-0.052	0.032	0.027
	(0.030)	(0.033)	(0.040)	(0.023)	(0.021)
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: Standard errors clustered at the UGP level in parentheses. All regressions include district and scheme fixed effects. 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 recieved training and dummies that control for access to local bureaucrats and connectivity through phone. The sample excludes spillover wards. The unit of observation is WM $\times$ scheme. Above Median Scheme Texts is a binary indicator equal to one if the treated WhatsApp group's scheme-specific message count (direct keyword classification) exceeds the median across all treated groups for that scheme. Control wards are assigned a value of zero. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table E2. **Learning Heterogeneity by Discussion Intensity for Each Scheme - Continuous**

	(1) **Formal Knowledge Index (std)**	(2) **Tacit Knowledge Index (std)**	(3) **Procedural Index (std)**	(4) **Best Practices Index (std)**	(5) **Combined Index (std)**
Treatment Ward	0.038*	0.025	0.053**	0.055***	0.052***
	(0.023)	(0.023)	(0.026)	(0.017)	(0.017)
Scheme Discussion (per SD)	0.020	0.008	-0.007	0.022*	0.021*
	(0.016)	(0.017)	(0.022)	(0.013)	(0.012)
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: Standard errors clustered at the UGP level in parentheses. All regressions include district and scheme fixed effects, WM-level controls (caste, baseline knowledge, same-district, block, GP indicators), and ward-level controls (ST/EBC reservation, age, gender, education). The sample excludes spillover wards. The unit of observation is WM $\times$ scheme. 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. Control wards are assigned a value of zero. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

F Attrition-Adjusted Estimates

The endline survey reached 6,213 ward members, compared to 7,277 at baseline. Table C21 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 evidene o difference is by caste: of those we find, the proportion of SCs is larger.

Next, we test if our endline responders are differ by treatment arms. Table C23 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 C21). 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 F1 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 **?**, 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–thereby bracketing the treatment effect under worst-case and best-case selection, respectively. Standard errors are again obtained via 500 cluster bootstrap replications. Results are reported in Table F3: we find that the upper bound of estimates are all large and the lower-bounds, though not always distinguishable from zero, are mostly positive.

F.1 AIPW - Doubly Robust Estimates

Table F1. **Attrition-adjusted treatment effects (doubly robust estimator)**

Outcome	Treatment effect	(SE)	N
Combined knowledge index	0.073***	(0.025)	4663
Confidence Index	0.089**	(0.043)	4413
Professional Networks Index	0.079***	(0.016)	4663
Bad Relationship with GP Head	0.041***	(0.013)	4641

Notes: Each row reports the doubly robust (AIPW) estimate of the treatment effect in the T vs C sample (spillovers dropped). 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 F2. **Attrition-adjusted spillover effects (doubly robust estimator)**

Outcome	Spillover effect	(SE)	N
Combined knowledge index	0.035*	(0.019)	4259
Confidence Index	0.011	(0.025)	4014
Professional Networks Index	-0.010	(0.016)	3593
Bad Relationship with GP Head	0.009	(0.009)	4240

Notes: Each row reports the doubly robust (AIPW) estimate of the spillover effect in the S vs C sample (treatment dropped). 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

F.2 Lee Bounds

Table F3. **Lee bounds for attrition (Treatment vs Control), residualised on controls + district FE**

Outcome	Lower bound	(SE)	Upper bound	(SE)	N{sel}
Combined knowledge index	0.036	(0.030)	0.132***	(0.027)	4415
Confidence Index	-0.032	(0.046)	0.177***	(0.046)	4413
Professional Networks Index	0.020	(0.023)	0.094***	(0.017)	4408
Bad Relationship with GP Head	0.020	(0.016)	0.052***	(0.016)	4641

Notes: Lee (2009) bounds computed using `leebounds` on residualised outcomes. Residuals come from `reghdfe` of the outcome on baseline controls determined using double lasso for each outcome with district fixed effects. Estimation sample drops spillovers (`SpilloverWard!=1`) and compares `TreatmentWard==1` vs `ControlWard==1`. Standard errors are obtained via cluster bootstrap at the GP level (`UGP`) with 500 replications. Stars are based on two-sided tests of each bound against zero: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table F4. **Lee bounds for attrition (Spillover vs Control), residualised on controls + district FE**

Outcome	Lower bound	(SE)	Upper bound	(SE)	N{sel}
Combined knowledge index	-0.066**	(0.031)	0.168***	(0.029)	4012

Notes: Lee (2009) bounds computed using `leebounds` on residualised outcomes. Residuals come from `reghdfe` of the outcome on baseline controls with district fixed effects. Estimation sample drops spillovers (`TreatmentWard!=1`) and compares `SpilloverWard==1` vs `0`. Standard errors are obtained via cluster bootstrap at the GP level (`UGP`) with 500 replications. Stars are based on two-sided tests of each bound against zero: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

G Appendix: Indices

G.1 Knowledge

We measure WM 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 (codified) steps and informal (tacit) practices commonly used in the field.[25] 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): waste management (LSBA), drains and lanes (Nali Gali), subsidised house construction (PMAY/MMAY), solar lights, subsidised food rations (PDS), pensions (old age pensions), and toilets (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.[26]

   We construct the Formal Knowledge Index as follows: 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 any WM for that scheme. We then take the average of these proportions across all schemes to obtain a single score for each WM. Finally, we standardize this score — by subtracting the mean and dividing by the standard deviation across all WMs in the control group — to construct the final index. See Table G1 for the questions included in the construction of the Formal Knowledge Index. The formal steps have the suffix "(F)".

2. **Tacit Knowledge Index**: Analogous to the Formal Knowledge Index, we construct a Tacit Knowledge Index using the same set of questions (Table G1) 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

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

[26] For 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.

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)".

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 questions on the Solar scheme (decision on number of lights and their placement), one on LSBA, and one on NREGA. 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 G3 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 G4.[27]

We construct the index in the following way: for each of six schemes (Toilet (SBM), Subsidised ration (PDS), Solar lights, Sanitation workers(LSBA), Piped water connections (Nal Jal), Job cards (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 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

[27] For 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.

enabling WMs to cultivate connections through the peer networks of fellow group members. We measure this using responses to the question: "How many WMs from outside your GP do you have conversations with regarding difficulties faced at work?" We standardize this measure — by subtracting the control group mean and dividing by the control group standard deviation — to obtain the Outside-GP WM Network Index.

2. **Block-Level Bureaucrat Network**: Navigating the administrative machinery requires WMs to interact with key block-level officials, particularly the Block Development Officer (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.[28] 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 within the Panchayati Raj system. We measure this using variable capturing a WM's links to political parties and including party membership. 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 - regarding whether they take help from WM of different GP in case of work related difficulty and re-standardizing the resulting score 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.

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

[28] For instance, construction works under PMAY or 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.

is constructed by standardizing the raw count using the control group mean and standard deviation. See Table G7 for details on the construction of the Confidence Index.

G.4 Citizen Assessments

We assess treatment effects on citizens' experiences with two categories of schemes: public goods provision (Nali Gali, Nal Jal, Solar Lights, and LSBA) and welfare programs (NREGA, PDS, Old age pensions, Toilet (SBM), and PMAY/MMAY). 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:

- ***Drains and lanes*** (***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.
- ***Tap water*** (***Nal Jal***): whether the household has received a water connection through the Nal Jal scheme, and if so, when.
- ***Solar Lights***: whether solar streetlights have been installed in the ward, and if so, in which years.
- ***Waste management*** (***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:

- ***Job Card*** (***NREGA***): whether anyone in the household has received a job card or applied for one since Holi 2023.
- ***Subsidised Ration*** (***PDS***): whether the household applied for or made any changes to a ration card since Holi 2023.

- ***Old Age Pension***: whether anyone in the household received or applied for an old-age pension since Holi 2023.
- ***Toilet*** (***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.
- ***Subsidised Housing*** (***PMAY/MMAY***): 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.

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 Ration*** (***PDS***): whether the household paid anything to receive the ration card.
- ***Toilet*** (***SBM***): whether the household paid anything to receive the toilet scheme benefit.
- ***Old Age Pension***:whether the household paid anything to receive the pension.

- ***Subsidised Housing*** (***PMAY/MMAY***): 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.

Table G1. Formal (F) and Tacit (T) Knowledge Index Questions (Part 1)

Question	Steps
If you want to get work done in your ward under the Nali-Gali Pakkikaran Yojana, 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 G2. 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 Pubic 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 G3. 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 G4. 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. *File a collective petition* 12. *Speak to Swachhta Grihi* 13. *Speak to Toilet data operator* 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. *Speak to Public Distribution System (PDS) Contractor* 13. *Speak to Marketing Officer (MO)* 14. *RTPS operator* 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 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. *Protest with citizens* 9. File online/ offline Complaint through Lok Shikayat Nivaran 10. *RTI* 11. *File a collective petition*	12. *Speak to a BREDA Company person* 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. *File a collective petition* 14. *Speak to Sanitation Supervisor* 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 G5. 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. *Speak to PS* 7. *Speak to JE of Public Health Engineering Department (PHED)* 8. *Speak to PHED Contractor* 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. *File a collective petition* 12. Speak to Panchayat Rozgaar Sevak (PRS)	13. *Speak to local groups/organisation (Sangathan)* 14. *Speak to MGNREGA data operato*r 15. *Speak to MGNREGA Block Program officer(BPO)* 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 G6. 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 G7. 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