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

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May 7, 2025

Abstract

Policies that broaden political representation empower new leaders who may lack knowledge of how government works. We study whether peer networks among local politicians facilitate knowledge transfer and improve the quality of governance. We run an experiment in partnership with the Government of Bihar, India, where we organised peer groups for randomly selected village leaders. We examine whether these peer networks increase politicians' knowledge of how to manage the development programs under their charge and improve the delivery of public services. We also test whether politicians from marginalised groups benefit more from peer networks. To understand mechanisms, we test if peer groups diffuse information about governance best practices and help politicians organise collective action.

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

JEL Classification codes: H4, H7, D73, D78, D83, D85
Study pre-registration: https://www.socialscienceregistry.org/trials/10926

*We are very grateful to Sawal Choudhary, Ria Dutta, Shivani Pandey, Vijay Prakash and Chanchal Kumar Singh for excellent research support. We also thank Jing Cai, Asim Khwaja, Michael Kremer, Martin Mattson, Karthik Muralidharan and Gautam Rao for feedback on the intervention and its design. We thank seminar participants at the Centre for Global Development for comments. We thank anonymous reviewers at the Weiss Fund and JPALGovernance Initiative. 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.

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1 Introduction

In recent decades, many developing countries have taken steps to broaden political representation. Common policies include decentralising power to lower tiers of government (Mookherjee, 2015) and introducing political reservations for marginalised groups (Chattopadhyay and Duflo, 2004). These policies have the potential to improve governance, by empowering disadvantaged groups and local leaders who better understand citizens' needs. But they also bring into the political system a cohort of leaders who may be unfamiliar with how government works. These local politicians, especially those from disadvantaged groups, may lack both knowledge about government processes and programs and the informal networks needed to navigate the state. Relaxing these constraints may help local politicians govern better, complementing policies that widen representation.

In this project, we examine whether peer networks enable local politicians to govern better. Prior work has shown that peer learning is important in many development contexts. Farmers' decisions to adopt new agricultural technologies are heavily influenced by their peers' choices (Foster and Rosenzweig, 1995; Beaman et al., 2021). Managers learn about business opportunities and best practices from their peers (Cai and Szeidl, 2018). Peers also facilitate learning in education (Duflo et al., 2011) and the workplace (Sandvik et al., 2020).

Similarly, peer politicians may be a natural source of information about governance best practices. Networks of local leaders may facilitate the diffusion of formal information (e.g. rules about how to manage funds and implement schemes) and tacit knowledge (e.g. how to navigate the local bureaucracy), both of which may help politicians deliver public services and solve citizens' problems more effectively. Indeed, many countries have associations or forums for local politicians to discuss shared concerns, exchange information and collaborate.[1] Despite their potential importance, we have very little empirical evidence on politician networks and their effects on local governance and economic development.

We experimentally evaluate how peer networks of local politicians affect the quality of local governance and economic development. Partnering with the Government of Bihar's Rural Development Department (RDD), we organise peer groups

[1]Examples include the US Conference of Mayors, the Association of Local Authorities in Mexico, and the National Front of Mayors (FNP) in Brazil. Indeed, it was FNP's annual convention that enabled Hjort et al. (2021) to evaluate the impact of distributing information about policy effectiveness to mayors.

for *ward members* (WMs), who represent a ward (consisting of about 1000 citizens) in their Gram Panchayat (GP) or village council.[2] WMs form the lowest (and most populous) rung of elected officials in India: there are over 100,000 WMs in Bihar alone and over 1 million in India. Developing a cost-effective and scalable way to improve their capacity and performance could thus yield significant benefits for rural Indians.

We designed our experiment with the aim of generating scalable insights (Muralidharan and Niehaus, 2017). Our sample of 7,719 WMs covered 18% of WMs in 10 districts and 26% of all GPs in Bihar, and we assigned 2,424 treated WMs to 206 peer groups. Our intervention was also co-implemented with the government department that will manage any future scale-up and was designed to capture within-GP spillovers.

Approximately 70% of WMs are first-time elected officials, and (due to political reservations) 63% are women or from disadvantaged Scheduled Castes (SCs). Our baseline data indicates that most WMs have limited knowledge about how to run the government schemes under their charge. The median WM knows only 40% of the steps required to implement the schemes they are supposed to manage. However, we also observe large variation in politician knowledge — bottom quartile WMs know only 28% of steps while top quartile WMs know 52% — suggesting considerable scope for peer learning.

Weak networks among politicians are a key friction impeding peer learning. Most WMs would like to discuss work issues with their peers, but in the absence of formal and informal channels, lack the ability to do so. As a result, while the vast majority of WMs speak to other WMs in their GP, only 18% have any contact with politicians from other GPs in their block. WMs must often interface with block- and district-level bureaucrats, who handle development funds and play an important role in program implementation, so WMs in different GPs could share insights on how to navigate their common bureaucracy. Indeed, comparing WMs in the same GP, we see that politicians with social ties to WMs in other GPs have 0.13 SD better knowledge about scheme management.[3] Our experiment tests whether this correlation partly reflects the causal effect of networks and examines how improved peer

[2]GPs are the smallest administrative unit in India, and in Bihar tend to consist of 4-5 revenue villages. The next highest administrative unit is a block, which consist of approximately 15 GPs. Above blocks are districts; each district consists of about 14 blocks.

[3]This correlation holds even after controlling for knowledge predictors like education, prior experience as WM, family political experience, and exposure to WM training.

networks impact public service delivery.

We randomly selected WMs to participate in peer groups with 10-12 other WMs from their district. Peer groups meet in person once every 8-9 months, have quarterly conference calls, and are part of a WhatsApp group. During meetings, WMs discuss issues they face and brainstorm solutions. A facilitator coordinates meetings and moderates the discussion, but all issues and solutions are raised by WMs themselves.

After 18 months, we estimate the impact of peer groups on three sets of outcomes — WM knowledge, the delivery of public services, and peer and citizens' assessments of governance quality. Using survey data at endline, we analyse whether having access to an expanded peer network makes WMs more knowledgeable about the programmes they are responsible for. To measure the quality of programme implementation, we use both administrative and survey data. Administrative data gives us information on (i) the number and timeliness of public works projects related to tap water, roads, sanitation, and streetlights and (ii) the details of citizens who receive benefits from various social programmes (e.g. pensions, subsidised food, workfare). We complement this by surveying citizens about the benefits they have received and eliciting their assessment of the public services delivered by, and the general performance of, their WM. We also elicit WMs' evaluation of the other WMs in their GP.

To shed light on mechanisms, we analyse issues discussed and solutions to governance problems shared during in-person meetings, conference calls and on the WhatsApp group chat. We assess whether peer groups facilitate the diffusion and adoption of governance *best practices* — i.e. practices that are highly correlated with good scheme implementation and adopted by high-performing WMs. Then, in our endline survey, we measure WMs' management practices and evaluate whether treated WMs are more likely to adopt best practices when implementing schemes.

We will introduce two additional interventions to learn about mechanisms. First, to provide further evidence that peer networks facilitate the diffusion of governance practices, we will cross-randomise an information intervention. We will inform WMs about a practice that improves governance in our context — filing grievances through Bihar's Public Grievance Redressal scheme, a government initiative to address citizens' complaints about public services. Experimental evidence shows that public service provision improves once WMs file a complaint (Sharan and Kumar, 2021). We will inform randomly-selected WMs in treatment and control about the scheme and tell these *informed WMs* how to file complaints on a citizen's behalf. We will test whether (i) information about grievance redressal circulates within peer networks and (ii) peer networks increase complaint filing among *informed* and *uninformed* WMs. The information intervention will help us understand whether peer groups not only facilitate information diffusion but also help politicians act on the information they already have.

Second, to test whether peer networks help WMs organise more effective collective action, we will nudge WMs to lead petitions. In many low-income democracies, local politicians mediate between their constituents and the state. In our context, WMs regularly file petitions on behalf of their constituents, typically demanding redressal of some public service failure. We will randomly select WMs in treatment and control, and nudge them to file petitions with the local bureaucracy on two issues: (i) improving implementation of a drinking water scheme and (ii) increasing training for new WMs. We will examine whether peer networks enable WMs to mobilise more support for their petitions.[4]

We plan to explore treatment effect heterogeneity along two dimensions. First, we examine whether WMs with links to political parties — who comprise 20% of our sample — benefit less from peer networks, since they are already connected to other politicians through their parties. This would provide suggestive evidence on the role parties play in local governance in developing countries, a relatively understudied question (Dal Bó and Finan, 2018; Gouvêa and Girardi, 2021).

Second, we examine whether peer groups have larger impacts on WMs from disadvantaged backgrounds — specifically SCs, who have weaker networks and knowledge at baseline. We oversampled SC WMs to ensure adequate power to detect treatment effect differences between SCs and non-SCs.[5] Since SC politicians usually represent wards dominated by SC citizens, our intervention could reduce inter-group inequalities if it yields greater benefits for SC politicians. Thus, if we find that SC WMs do indeed benefit more from peer groups, we will conduct two additional analyses. Specifically, we will test whether peer networks (i) reduce inequalities in access to public services between SC and non-SC citizens; (ii) en-

[4]Our pilot data suggests that WMs in treatment (i.e. peer groups) and control are equally willing to file a petition and have similar beliefs about issues (i) and (ii). Thus, we interpret any differences in the number of signatures in terms of WMs' ability to organise collective action.

[5]We do not examine treatment effect heterogeneity by gender because our pilot and baseline indicated that most female WMs attend peer groups with a male relative (usually their husband or son). Moreover, in a non-negligible share of cases, the female WM does not show up herself and the male relative attends in her stead.

hance the impact of political reservations for SCs (by combining our experimental variation with the exogenous variation of the rule for SC seat reservation).[6] This will help us understand whether informal peer networks among politicians complement formal policies to widen representation.

To shed light on how peer groups affect SC WMs, we randomly assigned treated SC WMs to either SC-only groups or mixed groups (which contained both SC and non-SC WMs). This variation enables us to test whether SC WMs primarily benefit from stronger ties to other SC leaders (who may offer solidarity and face similar governance challenges) or non-SC leaders (who tend to be more knowledgeable, experienced and connected).

Finally, our design allows us to examine within-GP spillovers. We randomised in two stages, first selecting GPs and then WMs within treated GPs. Our sample consists of WMs in peer groups (*treated*), WMs in treated GPs who are not in peer groups (*spillover*) and WMs from control GPs (*control*). Comparing the spillover and control samples provides an estimate of the spillover effects of our intervention.[7]

Contribution to literature. Our study relates primarily to the literature on peer learning. Economists have shown 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.

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

[6] This variation exploits cutoffs at various population thresholds Sharan and Kumar (n.d.).

[7] Generally, we expect positive spillovers: most WMs discuss work with their GP colleagues, so knowledge or best practices learned in peer groups may diffuse to untreated WMs in the same GP. However, there could potentially be negative spillovers for rivalrous schemes — for instance, if there are GP-level quotas and scarce slots are taken up by better-informed treated WMs.

between local leaders, and our findings will shed light on their impacts. In addition, we examine whether peer networks are especially valuable for politicians from disadvantaged groups. 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).

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.

The remainder of the paper proceeds as follows. Section 2 describes the background and context. Section 3 describes the research design, sampling and key hypotheses, while section 5 describes the data. Section 6 provides an overview of our estimation strategy and power calculations. Section 7 presents descriptive findings from our baseline survey, while section **??** describes limitations and challenges associated with the study. Section 8 concludes.

2 Background

2.1 Local Government in India

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

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 government. 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. 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). 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.

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 (NREGS). 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.

The state even has a formal Public Grievance Redressal scheme, through which citizens can file complaints about public service delivery failures. Sharan and Kumar (2021) describe how WMs use the scheme to flag implementation roadblocks that hinder the progress of public works in their wards. The scheme prescribes a clear process for resolving grievances: Grievance Redressal Officers — bureaucrats recruited specifically to manage this scheme — are assigned to cases and required by law to hold hearings and resolve complaints within 60 days.

Indeed, even for programs WMs formally manage, they must often negotiate with upper-level officials (like the Mukhiya and BDO) to release funds for project implementation.[8] Hence, a key aspect of a WM's job is to mediate between her constituents and the relevant upper-level officials who have de facto control of the allocation of public resources.

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

2.3 Scope for Peer Learning

Serving as WM is an entry-level political position, and the vast majority of WMs (68% in our sample) are first-time elected officials. Parties are officially not allowed to participate in GP elections in Bihar, and most WMs in our sample have no ties to any party.[9] Hence, most WMs lack knowledge of how government works and how to manage the schemes under their charge. We discuss this in more detail in section 7.

[8] 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.

[9] 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.

Several features of our context suggest scope for peer learning. First, even if WM knowledge is generally low, there will still be some experienced, knowledgeable WMs in our 10 districts, and other WMs can learn from them. Moreover, if each novice WM happens to know about a particular scheme or governance task, the collective knowledge of a group of WMs could nonetheless be significant.

Second, because a WM's role varies as policies change, formal training can become dated. In this dynamic environment, it is valuable to discuss ongoing concerns with other leaders facing the same governance challenges. For instance, at the start of the pandemic, WMs were suddenly asked to manage the COVID-19 pandemic in their GPs. Anecdotal evidence suggests that discussions with peers enabled WMs to learn about good practices.

Third, since most development activities are coordinated by district- and block-level bureaucrats, WMs in the same district often deal with the same bureaucracy. Sharing insights on how their shared bureaucracy works (e.g. how they expect forms to be filled, what information they require in a project proposal, which officer handles specific tasks) is another potential learning from peers.

At present, however, this potential for peer learning is unrealized. Most WMs only interact with other WMs from their own village: data from our baseline survey shows that 81.7% of WMs do not know or discuss work with any WM outside their village. Nevertheless, our pilot suggested that WMs in different GPs have a similar role, shared concerns and would benefit from exchanging ideas about how to do their jobs better.

Some WMs may benefit more from peer learning. Due to political reservations, over half of WMs are women and 20% are from Scheduled Castes (SCs). Yet gender and caste norms make access to resources, knowledge and networks harder for WMs of these groups. SC and female WMs could thus stand to gain more from expanding their peer networks. However, we only estimate differential treatment effects by caste and not gender, as our pilot and baseline indicate that most female WMs attend peer groups with, or are entirely substituted by, a male relative.

There are over 105,000 WMs in Bihar alone and over 1 million in India. Hence, if our peer group intervention succeeds in improving WM knowledge and governance, there is significant potential to scale.

3 Research Design

3.1 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.

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

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

3.2 Sampling

District Sampling

Our interventions runs across 10 districts of Bihar, which together account for 36% of the population of the state. These 10 were selected on the following criteria: (i) population and (ii) region. We pick the top 7 districts in terms of rural population[11]. The three additional districts increase representation of populations from the east[12] and the south[13]. Together, these 10 districts span 6 out of the 9 major divisions of Bihar.

[10] A district has, on average, 211 GPs and 2842 WMs.
[11] These are: Purbi Champaran, Muzaffarpur, Madhubani, Gaya, Samastipur, Saran and Darbhanga.
[12] Purnia and Banka.
[13] Jehanabad.

GP & Ward Sampling

Within districts, we followed a two-stage randomisation, first sampling GPs and then wards:

1. **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.[14] 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 B2).

2. **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 2).

3. **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.

4. **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. Also, our intervention was co-implemented with the government department that will manage any future

[14] 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.

scale-up. Collectively, these features of our design should improve the external validity of our study.

3.3 Main Comparisons

Our two-stage randomisation design allows us to estimate direct impacts of peer networks as well as spillovers. To estimate the direct effects of peer groups, we compare treated WMs against control WMs. To estimate spillovers, we compare untreated WMs in treatment GPs (whom we termed *spillover WMs* above) against untreated WMs in control GPs. For outcomes that we only observe at the GP-level, we compare outcomes in treated GPs against outcomes in control GPs.

4 Hypotheses and Key Outcomes

Our primary hypotheses are that peer networks improve politicians' knowledge and quality of governance. Below we describe the key outcomes we use to assess these hypotheses.

Hypothesis 1: Peer networks increase politician knowledge

Our baseline and endline survey of WMs measure peer networks. We ask each WM whom they discuss work-related issues with and what sort of information they exchange. This baseline data alone contributes to our understanding of social learning among politicians. We validate the *first-stage* of our intervention by testing whether treated WMs have stronger peer networks than control WMs at endline. In particular, peer networks with outside-GP WMs should increase.

Going beyond other studies of peer networks, we try to directly measure what WMs discuss and learn from each other through each interaction we facilitate — the in- person meetings, conference calls and WhatsApp group chats. Because our facilitators are present at these interactions, they are able to collect data on the key points exchanged by each WM during the in-person meetings and conference calls.[15] They also monitor all messages posted in the WhatsApp group. Taken together, these provide rich data on the information exchanged in peer groups: the governance issues discussed, problems raised, and solutions offered.

[15]We had two facilitators attend each in-person meeting. One facilitated the group discussion and was focused on engaging the WMs. The other took notes on who said what.

We measure WMs' knowledge of how to manage the key schemes under their charge. We hypothesize that peer networks enable WMs to learn how to do their job better. We also expect knowledge gains to be greater in groups with more active discussions and more knowledgeable peers and on topics where the group exchanged more information. Moreover, we identify governance best practices that are used by top-performing WMs, and test whether treatment causes WMs to adopt these practices.

Hypothesis 2: Peer networks improve the quality of governance

There is no single measure of governance quality. Thus, we combine objective metrics, such as WMs' implementation of public works and social protection programs and complement it with subjective assessments of governance from peer WMs and citizens.

Public works. WMs sanction and implement public works projects in their constituencies. We hypothesise that peer networks will help WMs learn how to better implement these schemes. Using administrative data on project implementation, we test whether networks enable WMs to implement these projects cheaper, better, and faster.

Implementation of Social Protection Programs. WMs are instrumental in getting their constituents access to a host of government schemes, including workfare (NREGS), subsidised food and housing, toilets and pensions. Through peer groups, WMs may learn more about the processes related to implementation of these social welfare programs (e.g. how to enroll beneficiaries, organise workfare (NREGS), get the phone number of the upper-level officer responsible for a particular scheme). Using administrative data, we measure the efficiency of service delivery.

Subjective Assessments of Governance Quality. Peer networks may enable WMs to deliver public services better and solve more of their constituents' problems. We elicit citizens' assessments of the WM's performance and the quality of governance in their ward. We can also test whether peer groups improve (perceptions of) governance quality for all citizens, or whether certain groups report being worse off.

We will also elicit peer assessments of WM knowledge, networks and governance quality from other WMs in the same GP.

Corruption. Our pilot suggests that, through peer groups, WMs will learn socially useful information (e.g. how to implement development programs) rather than socially harmful information (e.g. corruption strategies). In fact, if anything, our pilot suggests that WMs occasionally discuss strategies to mitigate corruption by upper-level officials (like the Mukhiya and BDO), whom they rely on to release development funds. Despite this, *ex ante*, the net effect of peer groups on corruption is ambiguous. We construct proxies for corruption using both administrative data (e.g. the amount of welfare benefits and government contracts received by a WM's family) and survey data (asking citizens about a WM's assets). In addition to these primary hypotheses, we also investigate secondary hypotheses related to heterogeneous effects and mechanisms.

Hypothesis 3: Weaker, less informed politicians benefit more from peer groups

Politicians from marginalised groups. Our pilot work suggested that politicians from marginalised groups (specifically SCs), who have weaker knowledge and social ties to other leaders, may benefit more from peer groups. Thus, we test whether knowledge, network and governance gains are greater for SC WMs.

It is unclear whether SC leaders will benefit more from increased ties to other SC WMs or to majority-group WMs. On the one hand, SC leaders may feel more comfortable voicing shared concerns (e.g. about discrimination) in an SC-only group. But they may gain from ties to upper caste leaders who tend to be more experienced, connected and knowledgeable. To assess the relative magnitude of both forces, we compare the outcomes of SC WMs randomly assigned to SC-only vs mixed groups.

Political Parties. A political party can be conceptualised as an organised peer network for politicians. WMs with party ties may thus benefit less from peer groups, since they already have an existing mechanism to connect with and access WMs in other GPs. About 20% of WMs in our sample have links to a political party, and we test whether they derive smaller gains from our intervention. This heterogeneity test provides suggestive evidence on the role that political parties play in local governance, including the diffusion of knowledge about how to govern.

Peer quality. We believe that governance-related information will diffuse via peer groups, raising politician knowledge. An implication, consistent with prior work (Cai and Szeidl, 2018), is that WMs assigned to groups with higher-quality peers should see greater knowledge and governance improvements. Treated WMs were randomly assigned to peer groups, creating exogenous variation in peer characteristics. We proxy quality in several ways, including baseline knowledge, prior experience, and education.

Hypothesis 4: Peer networks diffuse information and enable collective action

WMs play two key roles. First, they are scheme implementers, who manage programs that provide local public goods and a range of welfare benefits to their constituents. In this role, WMs require *information* about the de jure and de facto processes to execute these development programs. Second, they act as mediators between their constituents and higher tiers of government. This role requires that WMs negotiate with their Mukhiya, BDO, or other local officials. Their success often requires them to engage in some form of *collective action*, working alongside other WMs, to exert pressure on higher-level officials.[16]

We implement two experiments to directly test whether peer groups enable (i) diffusion of governance best practices (ii) WMs to organise more impactful collective action.

Information. To understand whether peer groups spread best practices, we will conduct an information experiment. We will tell randomly selected WMs (whom we call *informed WMs*) about a practice that has been shown to improve governance in our context — filing a grievance via Bihar's Public Grievance Redressal Scheme. In an experiment, Sharan and Kumar (2021) show that implementation of public works projects improves once WMs file a complaint. However, limited knowledge about the scheme and how to file complaints dampens grievance-filing rates among WMs.

We will contact informed WMs to (i) share details about the grievance redressal scheme, (ii) provide the phone number of a grievance facilitator who can help them file a complaint.[17] We will test whether WMs in peer groups are more likely to file

[16] For instance, since May 2023, WMs have been collectively protesting regarding lack of financial resources to maintain and implement the tap water scheme. Details are here.

[17] The team of grievance facilitators will be a fresh field team, unknown to either treated and control WMs.

grievances via our hotline.

Specifically, we will examine whether *uninformed WMs* (who were not told about the scheme) in a peer group are more likely to file grievances than uninformed control WMs. We will also observe if information about the grievance redressal scheme and hotline number are shared via the WhatsApp groups and during conference calls. We will also test whether informed WMs are more likely to file grievances when in a peer group. Taken together, this experiment will provide direct evidence about whether peer networks facilitate the diffusion of governance practices and enable WMs to act on information they already have.

Collective Action. We will run a second experiment to test if peer groups enable WMs to organise collective action. We will encourage randomly selected treated and control WMs (whom we refer to as *organiser WMs*) to get signatures on a petition that either (i) asks for more training and responsibilities for WMs or (ii) release of funds for completion of tap water projects. Such petitions are not atypical in our context. Organiser WMs will be told that their petition will be forwarded to officials in the Rural Development Department if it obtains more than 20 signatories.[18] Our proxy for the success of the collective action is the number of signatures a petition receives. We will test if peer groups enable WMs to mobilise more support for their petitions.

Hypothesis 5: There are within-GP spillovers

Since (i) we expect useful information to diffuse through peer groups, and (ii) most WMs interact with the other WMs in their GP, we believe that some knowledge that treated WMs acquire via their experimental peer groups will spread to their GP colleagues. We test for this by comparing the knowledge and governance quality of spillover WMs (i.e. untreated WMs in treated GPs) against those of controls WMs. We generally expect positive spillovers, there is the potential for negative spillovers for more rivalrous activities, such as social protection schemes which have an official or de facto GP quota for beneficiaries.[19]

[18] This is not deception: we will forward petitions to senior officials in the state capital with whom we are partnering to run this experiment and who oversee policies related to WMs' roles and responsibilities.

[19] However, prior work by Sharan and Kumar (2021) only finds evidence of positive within-GP spillovers.

5 Data

5.1 Baseline survey

Our baseline survey captured data across four main areas: demographic characteristics, networks, knowledge, and political participation.

Demographics. We collect data on each WM's education, marital status, caste, religion, primary income source, and electoral history, and the distance from their house to the district and block offices.

Networks and Exposure. We measure WMs' peer networks by asking them with whom they discuss work-related issues. We specifically ask about within-GP networks as well as networks outside the GP but within the same block and district. We also identify each WM's family ties to current and former elected officials and government bureaucrats, and their familiarity with local government officers like the BDO and *Vikas Mitra*. To capture WM's exposure to governance-related information, we measure their participation in government training, engagement with the digital eGramSwaraj application[20] and familiarity with WhatsApp.

Knowledge. We assess WMs' understanding of how to implement the development schemes they are supposed to manage. For each scheme, we construct a checklist of steps that are required to implement the scheme based on formal rules and discussions with local bureaucrats and high-performing WMs. For example, for the tap water scheme, there are 10 steps, which include preparing a list of beneficiaries within the ward, having an engineer prepare an estimated budget, and organising a public meeting to decide on the location of the borewells that will supply water for the tap. For the old-age pension scheme, there are 7 steps, including knowing the eligibility age, the three required documents, and ensuring name and date of birth match across these documents. Appendix C describes the knowledge metric for each scheme in detail.

Political involvement. Lastly, we examined WMs' participation in political parties, including which party a WM supports, membership in any party, involvement

[20]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.

in party activities, and whether the WM received any help from a party during the elections.

5.2 Data on Peer Group Interactions

We gather comprehensive data on peer group interactions by compiling data from in-person meetings, conference calls, and WhatsApp group chats.

In-person meetings and conference calls. First of all, we measure attendance, including whether WMs themselves attend, send a proxy, or bring someone along (often the spouse for female WMs).[21]

Second, we have 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.

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. 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 pilots, 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.

This data enables us to identify WMs who often offer solutions. We use this as a complementary measure of politician knowledge.

WhatsApp group activity. Each peer group has its own WhatsApp group. These 206 WhatsApp groups are managed by our moderators, whose main role is to ensure that discussions are civil and proceed smoothly. Moderators do not raise topics or offer solutions to any problems raised. So far, over 23,000 messages have been exchanged. WMs use the forum to ask questions regarding schemes, share progress

[21] To ensure we do not miss spillovers in our attendance notes, we capture whether the person attending with the invited WM is also a WM.

on issues raised in previous meetings, and exchange pleasantries, including festival greetings.

This data gives us a measure of the intensity of information exchange within each group, with some groups being more active than others.

5.3 Administrative data

5.3.1 Politician and Village Characteristics

Electoral data. Affidavits filed by candidates in GP elections allow us to observe politician characteristics such as name, age, gender, broad caste category, education, assets owned, and primary occupation. Electoral data tells us the votes polled by each candidate. We also know, for each constituency, the total number of candidates, caste and gender reservation status and total turnout. We will use some of these variables as controls.

Census data. We obtain information about GP characteristics from the most recent Indian census (2011). We capture each GP's number of villages, population, share of SCs/STs, distance from the nearest town and district HQ, availability of public goods such as government schools, primary health centres, roads and child-care centres. We add some of these variables as GP-level controls.

5.3.2 Implementation of Development Programs

We compile administrative data on several public works and social protection schemes where WMs play an implementation role. Table 9 outlines the schemes, the granularity of the data, and the outcomes we construct. The table shows that WMs are involved in delivering a wide range of public goods, ranging from roads and drains to sanitation and streetlights. For public goods schemes, we measure the number of projects completed and the time taken to complete them. Our administrative data generally does not allow us to measure project quality, a limitation we seek to address by eliciting (via a survey) citizens' perceptions of the quality of different public works in their ward.

WMs also play a role in helping their constituents access social welfare benefits, including pensions, workfare, subsidised food rations, and funds for toilet construction. For these schemes, we track the number of beneficiaries enrolled, or quantity of benefits delivered, during the treatment period. While the administrative data does not allow us to measure targeting quality, we use the citizen survey to compute exclusion and inclusion errors based on each citizen's characteristics and each scheme's eligibility criteria.

5.4 Endline WM survey

Our endline survey of WMs will collect some outcomes that we measured at baseline, such as WM networks and knowledge. However, we also extend these measures in certain ways.

Networks. Beyond the baseline measures, we will also ask WMs if they are members of associations called "ward member *sanghs*". We will also measure connections to higher-level politicians like state and national legislators — i.e. the MLA (Member of Legislative Assembly) and MP (Member of Parliament).

Knowledge. We will measure politician knowledge as in the baseline survey. We will ask questions on knowledge regarding scheme implementation and confidence in implementing various schemes. in In addition, we will collect data on best practices that are associated with good scheme implementation and adopted by high-performing WMs.

Public service delivery. We will ask WMs to report on activities conducted during the intervention period, and collect data on the quality of implementing public works and social protection programs. Specifically, we will enquire about (i) the status of new and ongoing public good projects; (ii) the number of applications filed on behalf of citizens to access welfare benefits (i.e. pensions, rations, workfare and housing). We will also ask WMs to evaluate other WMs in their GP on their networks, knowledge and governance.

Representation. We will measure whether WMs call public meetings (*ward sabhas*) to discuss policies and listen to their constituents' concerns. After a government order curtailing their role in implementing the tap water scheme, many WMs protested, demanding more responsibilities and financial devolution. We ask each WM whether they participated in these protests. We also ask WMs about other mobilisation activities they organised, including petitions filed with upper-level officials like the Mukhiya and BDO.

Aspirations and attitudes. Finally, we will also collect data on WMs' political aspirations, e.g. whether they plan to stand for re-election or run for another (higher) political office. Since our intervention promotes social contact with other politicians, including leaders from other communities, we will also collect data on WMs' stereotypes about and attitudes towards other groups.

5.5 Endline citizen survey

We survey citizens to capture their (i) assessment of public services in their ward; (ii) eligibility, application, and receipt of social welfare benefits; and (iii) views about their WM.

Public services. To complement our administrative data on the number of public works projects and speed of implementation, we survey citizens about the quality, usefulness, and maintenance of public goods the WM is involved in delivering. These include roads, drains, streetlights and sanitation. For instance, we ask citizens to assess the cleanliness and sanitation of their ward, both in absolute terms and relative to other wards in their GP. We also ask about specific inputs or processes the WM must do to deliver the public good. For example, for sanitation, we ask whether (i) a *Swacchta Karmi* (trash collector) has been hired and makes regular garbage collection rounds, and (ii) dustbins have been procured and distributed to households in the ward. As another example, to evaluate the quality of streetlights, we ask citizens (a) whether and how many lights have been installed in their ward, (b) if they are functional and (c) if citizens were consulted on where to place the streetlights. Appendix C.3 contains details of the metrics tracked for each public good scheme.

Social welfare. Complementing our administrative data on social welfare schemes, we ask citizens about the benefits they have applied for and received. This acts as a check against manipulated administrative records (Banerjee et al., 2020). In addition, we collect demographic and other characteristics that enable us to measure citizens' eligibility for different welfare schemes. This enables us to construct a measure of targeting quality, i.e. whether eligible citizens receive benefits. For each of the welfare schemes where WMs play a role — pensions, workfare (NREGS), food rations, and subsidies for housing and toilet construction — we ask citizens whether they have applied for the benefit, received benefits, and if the WM helped them access the benefit.

Representation. We construct a measure of how well WMs represent citizens based on how well (i) WMs understand citizens' needs and (ii) mediate between their constituents and the state. To capture (i), we elicit citizen preferences for different types of public goods and (in the WM survey) ask WMs to guess their constituents' preferences. We also measure WM-citizen interactions by asking citizens about the frequency of their interactions with their WM and whether the WM organises public meetings (*ward sabhas*).

To measure mediation, we enquire about WMs' efforts to raise citizens' problems to upper-level officials, like the Mukhiya and BDO. We ask whether citizens have requested help from their WM on any issue, and if their WM filed a petition with, or spoke with, a government official on their behalf. We also measure whether WMs ask citizens for bribes.

Overall evaluation of WM. Finally, we measure citizens' overall evaluation of their WM, both in absolute terms and relative to other WMs in the GP. We also capture whether the citizen voted for the WM and intends to do so in the next election (in 2026).

5.6 Do peer groups have persistent effects?

Our intervention may have been necessary to facilitate the initial contact between WMs, but the networks may remain alive and active even after we stop organising group interactions. Our endline survey will be conducted after WMs have been in peer groups for 18 months, at which point groups will have completed 2 in-person meetings and 4 conference calls. Thus, if we find that peer groups improve WM knowledge and governance at the 18-month mark, we plan to conduct a second endline a year later, to examine whether peer groups are self-sustaining and had persistent impacts even after our intervention ended.

6 Empirical Analysis

All equations below can be run at the ward or the citizen level depending on the data source, with appropriate modifications.

Our baseline regression is a standard ANCOVA specification, where we compare the outcomes of treated and control WMs and control for the level of the baseline outcome. In all specifications, standard errors are clustered at the GP level. All regressions include district fixed effects.

Direct effects. To estimate the direct effect of peer groups, we compare treated WMs (who are assigned to a peer group) against control WMs (in control GPs).

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

where $Y_{i,baseline}$ is the baseline level of the outcome variable and X_i are control variables for ward and WM characteristics, Δ represents district fixed effects.[22]

For outcomes relating to public good availability, we will estimate a slightly modified specification to account for the fact that some public goods are stocks rather than flows. For these stock public service outcomes, we will estimate the regression

$$Y_{it} = \alpha + \beta_1 \cdot TreatedWM_i + \beta_2 \cdot Post_t + \beta_3 \cdot TreatedWM_i \times Post_t + \theta X_i + \Delta + \epsilon_i \tag{2}$$

where the key coefficient of interest is β_3, the interaction between treatment and post.

Spillovers. To estimate spillovers, we compare untreated WMs in treated GPs (whose colleagues are in peer groups) against WMs in control GPs. That is, we restrict the sample to untreated WMs and estimate:

$$Y_i = \alpha + \beta \cdot TreatedGP_i + \gamma Y_{i,baseline} + \theta X_i + \Delta + \epsilon_i \tag{3}$$

Heterogeneous Effects. We investigate treatment effect heterogeneity along two dimensions — politician characteristics and peer group characteristics. First, we

[22] Ward-level controls include distance to nearest town, population, SC share and reservation status. Politician-level controls include demographisc like age, caste, gender and education.

test whether SC WMs benefit more from peer groups, estimating the regression

$$Y_i = \alpha + \beta_1 \cdot TreatedWM_i + \beta_2 \cdot TreatedWM_i * SC_i + \gamma Y_{i,baseline} + \theta X_i + \Delta + \epsilon_i \quad (4)$$

where the key coefficient of interest is β_2.

We estimate analogous regressions to test whether (i) WMs with ties to political parties benefit less from peer groups and (ii) we observe greater treatment effects for WMs who participate more actively in the peer group activities.

We will also causally test for whether being in an SC-reserved ward affects outcomes using the reservation algorithm to reserve wards for SCs. The algorithm used to reserve seats is analogous to the GP-reservation one described in (Sharan and Kumar, 2021). Essentially, there exists a ward SC population threshold above which a large number of wards are reserved for SCs and below which no wards are to be reserved. In practice, there is a statistically significant 25 p.p jump in the probability of SC reservation around the threshold. This gives rise to a fuzzy regression discontinuity design. We, therefore, estimate an RD-RCT style equation:

$$R_i = \alpha_0 + \alpha_1 1(Pop_i > T_b) + \alpha_2(Pop_i - T_b) + \alpha_3(Pop_i - T_b) * 1(Pop_i >= T_b) + \delta * X_i + b_i + \eta_i \quad (5)$$

$$Y_i = \alpha + \beta_1 \cdot TreatedWM_i + \beta_2 \cdot TreatedWM_i * R_i + \gamma Y_{i,baseline} + \theta X_i + \Delta + \epsilon_i \quad (6)$$

One other heterogeneous politician-level characteristic we will consider is distance to district headquarters. The peer meetings were conducted at the district HQ and distance from HQ was a determinant of participation.

Next, we analyse whether WMs benefit more when groups have higher-quality peers. We estimate the regression

$$Y_{ig} = \alpha + \beta_1 \cdot TreatedWM_i + \beta_2 \cdot TreatedWM_i * PeerQuality_{ig} + \gamma Y_{i,baseline} + \theta X_i + \Delta + \epsilon_i \quad (7)$$

where $PeerQuality_{ig}$ denotes a measure of the average quality of WMs in group g excluding WM i. We measure peer quality in a number of ways, including baseline knowledge, prior experience, education and number of peers in the group from own block/GP. We also investigate whether learning and performance gains on a particular issue or scheme are greater in groups that exchange more information, or spend more discussion time, on that subject.

We will also investigate if WMs are able to deliver their campaign promises better. To do so, we rely on our baseline data where we ask WMs to tell us issues they campaigned on. We will test to see if treated WMs are (i) more knowledgeable and (ii) able to better deliver better on campaign promises than control WMs using both endline survey data and administrative data.

For (i) above, for each scheme s and ward member i, we estimate:

$$\begin{aligned} Y_{is} = \alpha &+ \beta_1 \cdot \text{TreatedWM}_i + \beta_2 \cdot \text{Campaigned}_{is} \\ &+ \beta_3 \cdot \text{Campaigned}_{is} \cdot \text{TreatedWM}_i + \theta X_i + \Delta + \epsilon_{is} \end{aligned} \tag{8}$$

For (ii) above, for each citizen i, we will estimate for each scheme where we have reported outcomes on when a particular public good was delivered, the following regression:

$$\begin{aligned} Y_{it} = \alpha &+ \beta_1 \cdot \text{TreatedWM}_i + \beta_2 \cdot \text{Post}_t + \beta_3 \cdot \text{Campaigned}_i \\ &+ \beta_4 \cdot \text{Campaigned}_i \cdot \text{Post}_t + \beta_5 \cdot \text{Campaigned}_i \cdot \text{TreatedWM}_i \\ &+ \beta_6 \cdot \text{Post}_t \cdot \text{TreatedWM}_i + \beta_7 \cdot \text{Campaigned}_i \cdot \text{Post}_t \cdot \text{TreatedWM}_i + \theta X_i + \Delta + \epsilon_{it} \end{aligned} \tag{9}$$

We will run an analogous regression where we pool all schemes and add scheme fixed effects.

We will next test if treatment improves representation of citizen preferences. To do so, we rely on administrative data of schemes undertaken in treated and control GPs and test if being assigned to peer groups differentially affects scheme-related outcomes that citizens say they value in the citizen survey.

We are aware that we would have collected at best 2 citizens per ward - therefore our estimate of ward-level preferences may be noisy: since we typically have between 4 -6 (2) citizens in treated (control) GPs, we estimate the following regression:

To do so, we construct the total schemes undertaken/money spent in a GP on activities citizens report preferring (see Table 1 for an example of how we do this). We then run:

$$Y_g = \alpha + \beta \cdot TreatedGP_g + \theta X_g + \Delta + \epsilon_i \tag{10}$$

This fictitious example shows us how the GP-level averages are created based on citizen preferences and used in equation 10.

Table 1. Projects and Citizen Preferences at the Gram Panchayat Level

GPDP Unit	NalJal		NaliGali		Solar Street Lights	
	Total Projects	Total Value	Total Projects	Total Value	Total Projects	Total Value
UGP 1	4	6000	9	4000	9	4000
UGP 2	5	7000	8	6000	8	6000

GPDP Unit (Citizen)	NalJal	NaliGali	Solar Lights	Preferred Projects (Count)	Preferred Projects (Value)
UGP 1 (Emily)	1	1	0	13	10000
UGP 1 (Priya)	0	1	1	18	8000
UGP 2 (Paula)	1	0	1	13	13000

Note: Administrative data compiled from project MIS/GPDP plan documents. Citizen-preferred projects were recorded during structured interviews in the community survey.

Mechanisms. To test the learning mechanism, we restrict attention to uninformed WMs (i.e. who did not receive information about grievance redressal) and estimate whether WMs in peer groups are more likely to file complaints. This specification is analogous to the direct effects specification above. We also test whether informed WMs are more likely to file complaints when they are in a peer group (i.e. there is complementarity between information and networks), by estimating

$$Y_i = \alpha + \beta_1 \cdot Informed_i + \beta_2 \cdot PeerGroup_i + \beta_3 \cdot Informed_i * PeerGroup_i + \theta X_i + \Delta + \epsilon_i \tag{11}$$

To test the collective action mechanism, we also estimate a similar specification to the direct effects specification.

6.1 Power calculations

We estimate our statistical power to detect baseline treatment effects, identify heterogeneity, and test mechanisms. We perform power calculations in two steps: (i) we simulate data that matches the statistical properties of our main outcome variables (as inferred from our baseline data); (ii) then, we estimate the regression specifications described above on the simulated data.

Our power calculations rely on several assumptions. First, we assume an intra-cluster correlation (ICC) of 0.15. This is conservative since most variables in our baseline data have an ICC between 0.02-0.06. Second, we assume a baseline correlation of 0.1, i.e. that our controls absorb 10% of variation in the outcome. In our baseline data, controls absorb 10-30% of outcome variation, and our endline analysis will additionally control for the baseline level of the outcome variable, which will absorb further variation. Third, we assume 80-90% compliance with our treatment, and present power estimates for both 80% and 90% compliance. This is likely also conservative: measuring compliance through participation in conference calls and in-person meetings, we currently observe compliance of 94%, slightly higher than the level in Cai and Szeidl (2018).[23]

Table 7 presents minimum detectable effects (MDEs) in standard deviation units, while table B7 illustrates the magnitude of these SD effects in real terms for some outcomes. For our primary results — the direct impacts of peer groups on WM knowledge and governance quality — we are powered to detect treatment effects of 0.07-0.09 SD. These are smaller than the effects identified by similar studies. For instance, Cai and Szeidl (2018) find that peer groups improved firms' management practices by 0.2 SD and profits by 0.16 SD.[24] Our MDEs are also small in absolute terms. The average WM knows 27% of the steps required to implement schemes under their charge, and we are powered to detect a 1.35pp (4.8%) improvement in this measure of politician knowledge. Under the *Naligali* (drain construction) scheme, the average ward has 3.27 projects per year and each project takes 172 days to complete. We are powered to detect a 0.16 (4.9%) change in the number of projects and a 12.8 day (7.5%) change in implementation time. Our MDEs for spillovers are slightly smaller than this, and also smaller than the reference effect sizes.

Turning to heterogeneous treatment effects, we estimate whether SCs benefit more from peer groups, and oversampled SC WMs to increase power for this test. We are powered to detect a 0.15-0.17 SD difference in treatment effects, which is

[23]Specifically, when we measure compliance as participation in some peer group activity — either in-person meeting or conference calls — compliance is 94.2%. Using a stricter measure of compliance — e.g. attending an in-person group meeting plus at least one conference call or participation in all conference calls — we get compliance of 81.1%.

[24]This is likely due to our significantly larger sample. Cai and Szeidl (2018) sample 2,800 firms and match 1,500 into peer groups. We sample 7,719 WMs and match 2,424 into peer groups.

smaller than the caste difference in treatment effects estimated by a recent governance-related intervention in the same context (Sharan and Kumar, 2021). We have slightly less power to detect treatment effect differences between (i) SC-only and mixed groups and (ii) WMs with vs without ties to political parties. Our MDEs for these comparisons are 0.19-0.23 SDs.

Our additional intervention to directly test for the diffusion of information through peer groups has an MDE of 0.11-0.13 SD, which is smaller than the effect size in a similar intervention by Cai and Szeidl (2018). The intervention to test whether peer groups increase the ability to organise support for a petition has MDE of 0.15-0.18, which is lower than the mobilisation impact of leaders identified by Boudreau et al. (2021).

6.2 Empirical Contingencies

In this subsection, we describe how we plan to handle several empirical contingencies.

Outliers. We will winsorize the dependent variable at 1% in both tails of the distribution. For administrative data outcomes, such as project completion time, we will drop observations that are show indications of data entry errors (e.g. negative completion time).

Attrition. Administrative data gives us outcomes for WMs who do not participate in the endline survey. This both enables us to understand attrition patterns and measure treatment effects that are unaffected by attrition concerns. In addition, following common practice, we will show robustness of our treatment effects to Lee bounds (Lee et al., 2009).

Multiple hypotheses. To deal with concerns about multiple hypothesis testing, we follow ala Kling et al. (2007) and Anderson (2008) in constructing indices for key outcomes such as politician knowledge and scheme implementation. Appendix C contains details on the construction of these indices.

Experimenter demand effects. A natural concern is that treated WMs felt that they were expected to perform well, and inflated their performance in the endline survey. However, we also use administrative and citizen survey data on WM performance that is not subject to these demand effects.

Controls selection Following Belloni et al. (2014), we will estimate the impact of SJY by selecting the covari- ates using post double-selection lasso. The list of possible covariates includes ward member-level, ward-level, GP-level and citizen-level controls (for the citizen survey).

7 Results from the Current Data

7.1 Summary Statistics and Balance Tests

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 10, 11 and 12 present the results of balance tests. Table 10 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 11. 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 11 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 12 establishes balance over WMs' knowledge and pre-existing networks. The next subsection discusses these in greater detail.

7.2 WM Responsibilities, Knowledge and Networks

Responsibilities. As described in section 2, WMs' responsibilities often go beyond their *de jure* role. We included questions in the baseline survey to understand what schemes they are responsible for in practice. Table B1 provides a summary of the responses, and there appears to be significant variation. Nearly two-thirds of WMs identify the drains and lanes scheme as one they are responsible for and 54% identified the tap water scheme, while only 15% reported having a role to play in the pensions scheme. Nearly 20% of WMs state that they are not primarily responsible for any scheme.[25] The absence of clearly defined *de jure* responsibilities for WMs combined with large *de facto* variation suggests scope for peer learning.

Knowledge. We assessed WMs' knowledge on 6 schemes for which they have some responsibility. First, we identify the steps required to implement each scheme. Then, we calculate the share of required steps a WM is able to recount in our survey.[26] Table 1 shows that the average WM knows about 38% of the steps required to implement a scheme under their charge. However, this varies from 10% for the tap water scheme to 73% for subsidised food rations. Furthermore, we also see significant variation in knowledge across WMs: while bottom-quartile WMs know less than 28% of required steps, top-quartile WMs know 51%. This suggests that peer networks could enable learning, especially for less knowledgeable WMs.

Networks. While nearly all WMs report having work-related discussions with a fellow WM from their GP, networks outside the GP are weak. As shown in 12, the average WM can name only 0.19 WMs from other GPs within their block, 0.019 from other blocks in their district, and 0.005 outside the district (.[27] Moreover, we see that WMs from disadvantaged groups have weaker networks: SC WMs interact with 23% fewer WMs than WMs from more advantaged castes.[28].

Political parties are not allowed to participate in GP elections. Thus, all candidates contest as independents, and most WMs (80%, according to our baseline

[25]There are no statistical differences in responses to these questions between treatment, spillover and the control group.

[26]This approach is similar to the vignette-based method of measuring the quality of medical care, as pioneered by Das and Hammer (2014).

[27]Once again, there are no differences in pre-existing networks across treated, spillover and control WMs.

[28]These differences are driven entirely by differences in networks within the same block. As shown above, networks outside block are non-existent for both SC and non-SC WM's

survey) have no ties to any political party. Since most WMs in our context have no pre-existing ties to other leaders, and lack institutional mechanisms to form new ties, our intervention is likely to significantly expand the peer networks of treated WMs.

Relationship between networks and knowledge. Table B3 shows that peer networks are strongly correlated with baseline WM knowledge. Knowledge is measured by a standardised index across 6 key schemes. Adding a peer to a WM's network is associated with a 0.27 standard deviation increase in knowledge (column 1). This correlation remains strong even after controlling for other predictors of knowledge, such as prior political experience, education, training, and family ties to politicians and bureaucrats.

To validate our knowledge measure, we examine the association between baseline knowledge and whether politicians offer solutions to problems raised by their peers. Table B4 shows that more knowledgeable WMs are more likely to offer solutions. A 1 SD increase in knowledge is associated with a 25% increase in the number of solutions provided.

While these patterns help to validate our measures of peer networks and politician knowledge, they are purely correlational. Using our endline data, we will exploit our experimental variation to present causal evidence on the impact of peer networks.

7.3 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, some of whom travel up to 12 hours in the day to get to and from the meetings. Over 95% of treated WMs have participated in at least 1 peer group interaction (either in-person meeting or conference call), and 83% have participated in multiple interactions. Due to fog and other travel difficulties during the winter months, we saw slightly lower attendance (68%) during the first few weeks of the first in-person meeting. Conference calls have a higher attendance rate of about 80%. Table **??** contains a detailed breakdown of attendance by caste and gender. As mentioned previously, female WMs were significantly more likely to be accompanied or replaced by someone (usually their spouse). There are no significant differences in attendance across caste groups.

8 Conclusion

This pre-analysis plan evaluates the impacts of peer networks among politicians. Partnering with the Government of Bihar, we organised peer groups for 2,424 randomly selected village leaders. We study how peer groups affect politicians' knowledge, adoption of governance best practices, and delivery of public services. We test whether politicians from disadvantaged backgrounds gain more from peer groups. To identify mechanisms, we conduct two additional interventions to test whether peer groups facilitate the diffusion of governance-related information and enable politicians to organise collective action more effectively. We believe our paper provides the first experimental evidence on the impact of politician networks.

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A Main Tables

Table 1. Ward Member Knowledge

	N	Mean	25 Percentile	75 Percentile
Knowledge: Housing	7277	0.39	0.20	0.60
Knowledge: Drains and lanes	6486	0.20	0.00	0.33
Knowledge: Tap water	2150	0.10	0.00	0.20
Knowledge: Subsidised food rations	2770	0.73	0.50	1.00
Knowledge: Pensions	2772	0.51	0.43	0.71
Knowledge: Solar lights	6492	0.38	0.20	0.60
Knowledge Mean	7277	0.40	0.28	0.51

Note: This table displays, for each scheme, the share of total scheme-implementation steps a WM could list in the baseline survey. These schemes are part of our baseline knowledge index. For more on the knowledge index, see Appendix section C.

Table 2. 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 3. Summary of Hypotheses

#	**Hypothesis**	**Classification**
#1	Peer networks improve politician knowledge	Primary hypothesis
#2	Peer networks improve the quality of governance	Primary hypothesis
#3	Weaker politicians benefit more from peer groups	Secondary hypothesis
#4	Peer networks diffuse information and enable collective action	Secondary hypothesis
#5	There are within-GP spillovers	Secondary hypothesis

Table 4. Summary of Analysis Plan

Hypothesis	**Outcome Family**	**Index details**	**Regression equation**
#1	Knowledge index	Appendix C1, Table C1	Equation (1)
#2	i. Public works ii. Social protection iii. Citizen assessments	i. Appendix C2 ii. Appendix C2 iii. Appendix C3	Equation (1)
#3	i. Knowledge index ii. Public works iii. Social protection iv. Citizen assessments	i. Appendix C1 ii. Appendix C2 iii. Appendix C2 iv. Appendix C3	Equation (3) Equation (4)
#4a	Grievance redressal: knowledge, take-up	N/A	Equation (5)
#4b	Petition signatures	N/A	Equation (1)
#5	i. Knowledge index ii. Public works iii. Social protection iv. Citizen assessments	i. Appendix C1 ii. Appendix C2 iii. Appendix C2 iv. Appendix C3	Equation (2)

Table 5. Measures of Governance Quality (Part - 1)

Outcome family	**Data source**	**Component variables**	**Details**
Knowledge index	WM survey	*Steps required to implement:* i. Waste Management (LSBA) ii. Tap Water (Nal Jal) iii.Drains and Lanes (Nali Gali) iv. Subsidised House Construction (PMAY/MMAY) v. Solar Lights vi. Subsidised Food Rations (PDS) vii. Pensions (old age pensions) viii. Workfare (NREGA) ix. Toilets (SBM) *Best management practices:* i. Waste Management (LSBA) ii. Tap Water (Nal Jal) iii. Solar Lights iv. Subsidised Food Rations (PDS) v. Workfare (NREGA) vi. Toilets (SBM) *Government rules:* i. Waste Management (LSBA) ii. Solar Lights iii. Workfare (NREGA)	Appendix C1 We will break down steps into (i) procedural and (ii) tacit steps
Public works index	Admin data	*Admin data:* i. Waste Management (LSBA) ii. Tap Water (Nal Jal) iii. Drains and Lanes (Nali Gali) iv. Solar Lights	Table 9
Social protection index	Admin data	*Admin data:* i. Subsidised Food Rations (PDS) ii. Pensions (old age pensions) iii. Workfare (NREGA) iv. Toilets (SBM) v. Subsidised House Construction (PMAY/MMAY)	Table 9
Citizen assessment	Citizen survey	*Public works:* i. Waste Management (LSBA) ii. Tap Water (Nal Jal) iii. Drains and Lanes (Nali Gali) iv Solar Lights v. Anganwadi vi. Asha worker vii. Primary health centre viii. Primary government school	Appendix C3

Table 6. Measures of Governance Quality (Part - 2)

Outcome family	Data source	Component variables	Details
Citizen assessment	Citizen survey	*Social protection:* i. Subsidised Food Rations (PDS) ii. Pensions (old age pensions) iii. Workfare (NREGA) iv. Toilets (SBM) v. Subsidised House Construction (PMAY/MMAY) *Other aspects of governance:* i. Representation ii. Overall rating of WM performance	Appendix C3

Table 7. Power calculations

Effect	Data	MDE (90% comp.)	MDE (80% comp.)	Ref. eff. size (SD)
Direct impact	Survey	0.08	0.09	0.2 (Cai and Szeidl, 2018)
Direct impact	Admin	0.07	0.08	0.16 (Cai and Szeidl, 2018)
Spillovers	Survey	0.08	0.09	0.17 (Sharan and Kumar, 2021)
Spillovers	Admin	0.06	0.07	0.17 (Sharan and Kumar, 2021)
Het TE: SCs	Survey	0.16	0.17	0.21 (Sharan and Kumar, 2021)
Het TE: SCs	Admin	0.15	0.16	0.19 (Sharan and Kumar, 2021)
SC-only vs mixed	Both	0.21	0.24	N/A
Het TE: party	Both	0.19	0.21	N/A
Learning	Behavioural	0.11	0.13	0.46 (Cai and Szeidl, 2018)
Collective action	Behavioural	0.15	0.18	0.27 (Boudreau et al., 2021)

Note: This table presents estimates from power calculations. Column 1 shows the treatment effect that the power estimate is for. Column 2 shows the type of data used for the power estimate. Columns 3 and 4 present minimum detectable effect (MDE) estimates in standard deviation units, assuming compliance with treatment of 90% and 80% respectively. Column 5 presents reference effect sizes that similar interventions have found.

Table 8. Aspects of Peer Quality

Dimension of Quality	**Measure of Peer Quality**
Baseline knowledge	• Average baseline knowledge of other WMs in group • # of high-knowledge peers (baseline knowledge >80th percentile) in group • Dummy for whether group has >median baseline knowledge • Dummy for whether group has >median # of high-knowledge peers
Prior experience	• # of other WMs in group who have previously served as WM • Dummy for whether group has >median # of WMs with prior experience
Education	• Average education of other WMs in group • Dummy for whether group has >median average education
Baseline networks	• # of WMs with at least one connection outside GP at baseline • # of WMs with at least one connection to block office at baseline • Dummy for whether group has >median # of WMs with outside-GP connections • Dummy for whether group has >median # of WMs with block office connections
Index	• Z-score of peer quality • Dummy for whether group has >median peer quality z-score

Table 9. Public Service Delivery outcomes (Administrative Data)

Scheme	Description	Granularity	Outcome: Admin Data
Lohiya Swachha Bihar Abhiyan (*LSBA*)	Solid waste management	GP Ward	*GP*: # wards where dustbins are procured, distributed *Ward*: # cleaners hired, collection started
Nal Jal	Tap water for each household	Ward	# of households connected Project completion time
Nali Gali	Drains Concrete lanes	Ward	# projects Project completion time Cost over-runs
Solar Light	Streetlights	Ward	# lights installed
Pensions	Monthly pension for eligible groups (elderly, widows, disabled, etc)	Ward	# of beneficiaries
Swachh Bharat Mission (*SBM*)	Subsidy for toilet construction	GP	# toilets constructed
Workfare (*NREGS*)	Guaranteed employment at minimum wage up to 100 days per year	GP Individual	# workdays # job cards # projects
Rations (*PDS*)	Subsidised food for eligible HHs	GP Individual	# ration cards # PDS rice & wheat purchased
Pradhan Mantri Awaas Yojana (*PMAY*) *Mukhya Mantri Awaas Yojana* (*MMAY*)	Subsidy for house construction	Individual	# houses constructed
Gram Panchayat Development Program (*GPDP*)	Panchayat annual planned activities	Ward/GP	# activities planned # amount spent

Note: This table describes, for each scheme in the administrative data, the type and granularity of outcomes we can measure.

Table 10. 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 11. 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 12. 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.

B Appendix: Additional Tables

Table B1. WM's stated Responsibilities

Government Schemes	**Responsibility**
Drains and lanes	63.2%
Tap water	54.4%
Pension	15.6%
Subsidised food rations (PDS)	8.7%
Subsidised house construction	21.3%
Subsidised toilet construction	16.3%
Workfare employment (NREGA)	9.0%
Solar light	13.0%
No scheme	18.0%
Others	9.7%

Note: This table summarizes WM's responses from the baseline survey to the question: "What schemes are you responsible for the implementation of?" This was a multiple-response question.

Table B2. 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 B3. Network-Knowledge Correlations in Baseline Survey

	(1) **Knowledge Index**	(2) **Knowledge Index**	(3) **Knowledge Index**
Networks: All	0.271***		
	(0.022)		
Networks: Block		0.294***	0.257***
		(0.025)	(0.024)
Networks: Dist.		0.106	0.076
		(0.076)	(0.076)
Networks: State		0.253	0.265
		(0.195)	(0.189)
Constant	-0.063***	-0.065***	-0.057***
	(0.013)	(0.013)	(0.012)
Observations	7277	7239	7239
Fixed Effects	Dist X Strata	Dist X Strata	Dist X Strata
Controls	NO	NO	YES

Note: Table plots correlations between our network variables and the knowledge index. The Knowledge Index is a standardized index of WM's knowledge on 6 key schemes, i.e. housing (PMAY: the main housing scheme), drains/lanes implementation (Naligali Yojana), solar lights scheme, tap water, PDS (rations) and pensions. We first identify the steps involved in carrying out these activities. We then calculate the share of the total steps a ward member is able to recount in our survey. The index is the standardized sum of shares across these schemes. 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. Regressions have district and strata (SC/non-SC ward member) FE. In Column (3), we also control for caste, education and previous political experience of WMs. We cluster errors at the GP level.

Table B4. Knowledge-Solution Correlations from Baseline Survey/In-Person Meeting Notes

	(1) **Mean Solutions**	(2) **Mean Solutions**	(3) **Mean Solutions**	(4) **Mean Solutions**
Knowledge Index	0.024***	0.024***		
	(0.004)	(0.005)		
Knowledge: Housing			0.070***	0.055**
			(0.026)	(0.026)
Knowledge: Drains and Lanes			0.105***	0.089***
			(0.023)	(0.023)
Knowledge: Solar Lights			0.010	0.003
			(0.016)	(0.017)
Constant	0.096***	0.096***	0.044***	0.056***
	(0.004)	(0.004)	(0.011)	(0.011)
Observations	1473	1473	1355	1355
Fixed Effects	None	Dist X Strata	None	Dist X Strata
Controls	NO	NO	NO	YES

Note: This table plots the correlation between our knowledge index (columns 1-2) and its components (columns 3-4) and the mean number of solutions ward members propose on any issue discussed in the in-person meetings. Most meetings had discussions on up to 7 issues. The Knowledge Index is a standardized index of WM's knowledge on 6 key schemes, i.e. housing (PMAY: the main housing scheme), drains/lanes implementation (Naligali Yojana), solar lights scheme, tap water, rations (PDS) and pensions. We first identify the steps involved in carrying out these schemes. We then calculate the share of the total steps a ward member is able to recount in our survey. The index is the standardized sum of shares across these schemes. Regressions have district and strata (SC/non-SC ward member) FE where mentioned. We cluster errors at the GP level. Regressions are run only for members who show up to our first round of in-person meetings.

Table B5. Attendance of Meetings by Type and Demographic Group (Percent)

Meeting Type and Attendance Status	Male (N = 1146)	Female (N = 1277)	SC (N = 808)	Non-SC (N = 1616)	Total (N = 2424)
In-person 1					
Present	59.51	25.61	45.05	39.91	41.63
Replacement	3.84	34.69	16.09	22.15	20.13
Absent	36.65	39.70	38.86	37.93	38.24
Conference Call 1					
Present	77.23	20.28	47.90	46.84	47.20
Replacement	1.48	59.20	29.83	32.98	31.93
Absent	21.29	20.52	22.28	20.17	20.87
Conference Call 2					
Present	74.13	17.90	45.32	44.60	44.86
Replacement	2.70	60.72	30.94	33.26	32.36
Absent	23.17	21.38	23.74	22.14	22.79
In-person 2					
Present	72.34	21.77	44.18	36.94	39.36
Replacement	3.84	47.38	28.84	30.75	30.12
Absent	23.82	30.85	26.98	32.30	30.53
Conference Call 3					
Present	75.04	18.75	45.15	45.56	45.41
Replacement	2.96	58.02	30.25	32.10	31.39
Absent	22.01	23.22	24.60	22.35	23.20
Conference Call 4					
Present	76.35	20.85	47.33	47.03	47.14
Replacement	1.57	57.56	29.80	31.92	31.14
Absent	22.08	21.59	22.87	21.05	21.72

Note: This table displays attendance rates for ward members across our rounds of interactions: (i) in-person meetings and (ii) conference calls. Columns 2 and 3 show breakdowns by gender; columns 4 and 5 by caste. "Replacement" indicates that the WM sent someone else to attend. This was overwhelmingly the case for female ward members.

Table B6. Correlates of Attendance

	(1) **At least One**	(2) **At Least One (In-Person)**	(3) **At Least One (Call)**	(4) **Mean Attendance**
EBC	-0.013	-0.045	-0.032	-0.022
	(0.015)	(0.035)	(0.020)	(0.021)
ST	-0.002	-0.143	0.022	-0.000
	(0.039)	(0.099)	(0.039)	(0.054)
SC	0.002	-0.001	0.003	-0.001
	(0.011)	(0.029)	(0.015)	(0.018)
BC	0.004	-0.005	-0.002	0.009
	(0.010)	(0.026)	(0.013)	(0.016)
Female	0.006	-0.021	0.005	0.002
	(0.008)	(0.019)	(0.010)	(0.011)
Years of Education	0.002	0.003	0.002	0.001
	(0.001)	(0.003)	(0.002)	(0.002)
Distance to District Headquarters	-0.000	-0.004***	0.000	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
SC Only Group	-0.005	-0.044	-0.008	-0.016
	(0.013)	(0.033)	(0.017)	(0.020)
Knowledge Index Z Score	0.003	0.028***	0.003	0.010*
	(0.004)	(0.010)	(0.005)	(0.006)
Constant	0.943***	0.806***	0.910***	0.784***
	(0.018)	(0.041)	(0.022)	(0.026)
Observations	2312	2312	2312	2312
Fixed Effects	Dist	Dist	Dist	Dist

Note: This table plots the correlation between attendance metrics and ward member characteristics (caste, gender, years of education, distance to district headquarters, SC-only member group status, and the knowledge index at baseline). The reference caste category of the ward member is general caste and the reference ward member gender is male. The distance to district headquarters is in kilometers. Regressions have district FE where mentioned. We cluster errors at the GP level. Regressions are run only for treated ward members.

Table B7. Summary statistics for key outcomes

Outcome	Mean	Std dev	MDE for direct TE (80% comp.)
Knowledge (%)	27	15	1.35pp
Networks (#)	3.20	1.51	0.13 contacts
Naligali (# projects)	3.27	2.01	0.16 projects
Naligali completion (# days)	171	160	12.8 days

Note: This table contains summary statistics for several key outcome variables, using data from our baseline survey and administrative data sources. The units of the outcome are indicated in brackets next to the outcome. The MDE column indicates the minimum detectable effect size for the direct impact of peer groups, assuming 80% compliance with our intervention.

C Appendix: Indices

C.1 Knowledge Index

In our **baseline survey**, we created a knowledge index in the following manner. We focused on six schemes:

1. Tap Water (Nal Jal)
2. Drains and Lanes (Nali Gali)
3. Subsidised House Construction (PMAY/MMAY)
4. Solar Lights
5. Subsidised Food Rations (Public Distribution System; PDS)
6. Pensions (old age pensions)

For each of these schemes, we asked WMs to list the steps to be undertaken in order to implement them. We then calculated the share of total steps a ward member could name for each scheme. Following Kling et al. (2007), we created a normalized index out of these shares: we calculated the z-score for each individual scheme share and averaged it across all schemes mentioned above.[29]

For the **endline survey**, we will create a new knowledge index and expand the set of schemes we ask information about. We add the LSBA waste management scheme, since it has emerged to be a key area of WM involvement. We will also ask about implementation of toilet construction (SBM) and the workfare (NREGS) schemes, both of which WMs have some role to play in. Thus, we now focus on the following schemes:

1. Waste Management (LSBA)
2. Tap Water (Nal Jal)
3. Drains and Lanes (Nali Gali)
4. Subsidised House Construction (PMAY/MMAY)

[29] In our baseline survey, we did not ask about all schemes to all WMs. 25% of WMs were asked about all schemes. Our measure of knowledge for each WM is a function of as many schemes we asked them questions about.

5. Solar Lights
6. Subsidised Food Rations (PDS)
7. Pensions (old age pensions)
8. Workfare (NREGA)
9. Toilets (SBM)

As before, we will ask WMs to list the steps to be undertaken in order to implement these schemes. We will then calculate the share of total steps a ward member can name for each scheme. Our knowledge index will be of two types:

1. **Normalized Index**: following (Kling et al., 2007), we will calculate the z score for each individual scheme share and average it across all schemes mentioned above.
2. **PCA Index**: We will create a PCA index of all shares.

In our analysis, we will control for baseline knowledge and show robustness of all our endline results to only restricting information regarding schemes we asked them about at baseline.

C.1.1 Questions

Table C1. Knowledge Index Questions

Question	Choices
What are the steps to start the Nali-Gali scheme in your ward?	1: WM identifies potential sites for implementation 2: WM arranges the ward sabha and finalizes the implementation sit--es 3: Junior Engineer (JE) prepares the budget statement 4: Block Office approves and transfers funds to WM 5: Panchayat Sevak and Mukhiya sign documents 7: WM withdraws funds, prepares the Measurement Book (MB) 8: After MB completion, remaining funds withdrawn
What are the steps to start the Nal-Jal scheme in your ward?	1: Block office prioritizes wards 2: WM conducts a beneficiary census 3: Engineer estimates for selected ward 4: Ward Sabha determines drilling location 5: Funds sent to Mukhiya based on estimates 6: Mukhiya deposits share in WMIC account 7: Contractor selected by WM/Mukhiya 8: Work begins, Measurement book for the first installment prepared 9: Audit conducted, remaining funds transferred
What are the steps to start the Solar Light scheme in your ward?	1: Each ward installs 10 solar lights 2: Sequential installation: Wards 1-4, 5-9, and so forth 3: Ward member compiles list, submits to Mukhiya 4: Ward Sabha finalizes installation sites 5: Mukhiya and Panchayat sevak sanction lights upon receipt from t--he state
What are the steps to apply for Vridha Pension Yojana?	1: Age requirement: 60 years and above 2: Bring photocopies and original Aadhar Card, Voter ID, and bank passbook 3: Ensure matching names in all three documents 4: Align date of birth on Aadhar and Voter ID 5: Apply at RTPS counter in block office/CSC/online via state service pension dept. website
What are the steps to apply for a Ration Card?	1: Bring original and photocopy of Aadhar card and passbook 2: Have family group photos. (at least one) 3: Apply at the RTPS counter at the block office/CSC/online on e-pds website
What are the steps to apply for Awas Yojana?	1: Ward Member compiles eligible Households list 2: This list is added to the already existing list at the GP level 3: Mukhiya decides final beneficiaries based on fund availability 4: Mukhiya submits list to Indira Awas Sahayak

Note: This table lists the set of questions and choices from our baseline survey that form the basis for the knowledge index.

C.2 Scheme Index

We will create two separate scheme indices based on the admin data (see Table 9 for a description of outcome variables from the admin data): (i) public works index

(ii) social protection index.

For public works, we will combine scheme outcomes across the following schemes: Tap water (Nal Jal), Drains and Lanes (Nali Gali), Solar Lights and waste management (LSBA). Data on all public goods is currently viewable at the ward level, so our index will also be at the ward level.

For social protection, we will combine scheme outcomes across the following schemes from the admin data: pensions, rations, housing, NREGA and toilets. Separate indices will be created for GP- and ward-level outcomes.

C.3 Citizen Assessments

We create an index that captures citizens' assessment of public good provision in their ward. For each public good the WM is involved in providing, we ask citizens about the quality of implementation of the relevant scheme and aggregate their views into an index (following Kling et al. (2007)). We then construct an overall index across all types of public goods. Below we describe the variables used to measure the quality of each public good.

- ***Nal Jal***: whether household has access to piped tap water; quality of pipes laid; coverage of piped water across the ward; how useful is piped water to household

- ***Nali Gali***: were drains built in the ward; were village lanes constructed in the ward; what is the quality of drains and lanes; rating of maintenance of drains and lanes; subjective assessment of implementation quality; how useful is having these drains and lanes.

- ***Solar lights***: whether solar lights have been installed in ward; how many lights have been installed in ward; whether solar lights are functional; whether citizens were consulted on where to place the streetlights; subjective assessment of implementation quality; usefulness of having streetlights.

- ***LSBA***: whether *Swacchta Karmi* (trash collector) has been hired; regularity of *Swacchta Karmi* garbage collection rounds, whether dustbins have been procured and distributed to households in the ward; number of soak pits created in ward during intervention period; quality of soak pits constructed; subjective assessment of cleanliness and sanitation management; usefulness of having garbage collection provided

- ***Anganwadi***: whether childcare centre opens daily; has dedicated staff; provides quality education; provides rations to children

Second, we create an index for citizens' evaluation of the implementation of social welfare programs. We cover four key welfare schemes, namely subsidised food rations (PDS), pensions, workfare (NREGS), and subsidies for house construction (PMAY) and toilet construction (SBM). For each scheme, we measure whether the household has (i) applied for benefits, (ii) obtained benefits and (iii) whether the WM helped the household in accessing these benefits.

Third, we elicit citizens' overall evaluation of their WM in absolute terms and relative to other WMs in the GP. We also measure citizens' assessment of WM performance on domains other than the delivery of public services, such as the quality of representation, the ability to mediate with upper-level officials, and their availability and effort on behalf of constituents. As in the case of the knowledge index and scheme indices, we will follow (Kling et al., 2007) to create a standardized index of questions measuring citizen assessment of WMs and estimate treatment effects on this index.

C.4 Caveats

While we are confident that this is the list of welfare schemes and public goods that WMs are responsible for, our work over the past year has suggested that WMs work in a very dynamic environment, making it somewhat hard to exactly pinpoint the relative importance of various schemes and public goods.

For instance, when the intervention was rolled out in January 2023, WMs were focused on setting up the bank accounts for their wards – a key topic of discussions in our pilot meetings. However, 11 months into the intervention, ward bank accounts are no longer a major point of discussion. This has occurred for two reasons: first, many WMs have managed to set up ward accounts in the past 12 months; second, the cabinet order of May 2023 that took away financial powers to implement the tap water scheme and the drains and lanes scheme meant that setting up ward banks accounts is not a key concern. Moreover, while WMs continue to maintain and monitor water pipes and household taps under the tap water scheme, the absence of new financial resources to wards has meant that it is lower in the pecking order than the waste management scheme. WMs' role in the waste management scheme was somewhat unexpected too: they were chosen to be chief implementers of the policy in mid-2023.

Another reason for varying relevance of schemes is lack of funds in the state treasury: for both the housing scheme and toilets, there is currently no funds allocated to GPs (let alone wards). Officials in the Bihar government do not see this changing in the near future. This is somewhat unfortunate because ward members play a central role in beneficiary selection for both these schemes, in addition to acting as intermediaries that liaise with the local state on behalf of citizens.