Updating the State: Information Acquisition Costs and Social Protection Delivery

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Abstract

Digital payment systems are frequently described as a means of expanding state capacity in lower-income countries; however, program performance gains may be weakened if digitization reduces (or leaves unchanged) program information available to overworked administrators responsible for financial oversight, or if it increases middle managers' informational advantage over the principal. To assess these concerns, we conduct an at-scale field experiment in two Indian states, varying the administrative level provided access to *PayDash*, a mobile-based e-management platform that lowers program information acquisition costs. *PayDash* access cuts payment processing time by 11 percent, increases work days by 19 percent, and leaves program corruption unchanged. Manager and principal PayDash access had similar impacts, suggesting information gains directly improved program implementation by middle managers. A transfer-tracking exercise shows a 23 percent reduction in middle-manager transfers, suggesting that lowering information acquisition costs for the principal reduces her reliance on blunt incentive contracts.

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1 Introduction

Government-to-person (G2P) transfers are becoming an increasingly important component of low income countries' social protection architecture, with digital processing gaining favor as a way to build state capacity to make these transfers (Gentilini et al. 2020).[1] Administrators, on the other hand, are typically still involved in authorizing G2P program fund disbursements and may find that automating some, but not all, aspects of program implementation disrupts their access to information. Higher-level administrators who are no longer directly involved in payment processing may lose visibility on beneficiary selection processes in villages, and heavy work loads may limit their ability (or interest) in obtaining this information. As a result, their ability to ascertain whether payment delays, for instance, reflect village-level implementation issues or rent-seeking by middle managers with fund approval powers may be impeded, eventually lowering program benefits accruing to citizens.[2]

In this context, the impacts of easing access to program information for administrators will depend on the nature of underlying agency concerns. If the main bottleneck is that middle-managers and the principal are less informed about implementation challenges at the local level, then lowering information search costs for either principals or middle managers could improve monitoring and reduce delays. If the major issue is shirking or rent-seeking by middle management, the value of improving information will vary with the level of hierarchy at which it is delivered. Finally, if the principal is also designing incentive contracts for middle-manager and is aiming to lower her own search costs, then improving information available to her can also reduce the principal's use of high-powered incentive contracts (Carroll and Bolte 2020). Given low-income bureaucracies' limited ability to utilize financial and other career incentives (e.g., promotions, firing), the canonical example of such an incentive in these settings is the use of posting transfers (Iyer and Mani 2012; Khan et al. 2019).

In this paper, we report on a large-scale experimental evaluation that spanned Madhya Pradesh and Jharkhand, two North Indian states with approximately 120 million people, 25 million of whom are rural poor. The experiment involved administrators of the world's largest rural workfare pro-

[1] Gentilini et al. (2020) documents 1,841 such programs in 214 countries in 2020, with digital (G2P) transfers accounting for a growing share of these payments.For example, 63 percent of Covid-related transfers in low- and middle-income countries were made through digital infrastructure.

[2] Banerjee et al. (2020) find transitions to e-governance in internal funds transfers actually increased payment delays from a worker perspective.

gram, the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS).[3] Administrators must enter and authorize MGNREGS worker payments, after which the bank processes and delivers them into worker accounts digitally. Within a state, district administrators function as effective principals for the fund allocation process and their primary role is as monitors. Payment approvals are delegated to sub-district officials and program implementation to village council, or Gram Panchayat (GP), officials. In collaboration with Indian government counterparts, we developed a mobile-based management platform for MGNREGS, known as PayDash. The platform uses "digital exhaust", which is generated by timestamps that log user activity in the MGNREGS digital administrative system, to track when each bureaucratic step of the worker payment process is completed for each workspell. By packaging information in an accessible and actionable format, PayDash reduces time costs incurred in learning about where a payment delay is occurring as well as who is responsible for the current step in the payment process. The district served as the randomization unit in each state. We randomly assigned districts to one of four groups: control and three treatment groups. The treatment groups varied in the level of administrative hierarchy at which we provided PayDash access - at the district (the relevant principal) level, subdistrict (middle manager) level, or both.

We calculate our major program outcome measures, overall processing time and work provision, using administrative data on payments from one year preceding our intervention through the end of our assessment period, which includes more than 19 million payrolls. In the year prior to our intervention, officers' took twice as long to process payments as the central government's stipulated 8-day threshold. Relative to control districts, treatment districts saw a 1.4 day reduction in time to complete steps under bureaucrats' purview (11 percent of the control at baseline), and a 7 percentage point (10 percent) decline in the probability of their completion being officially considered late. In addition, the average number of beneficiary person-days worked increased by 19 percent in treatment districts. The share of government-submitted payment requests subsequently rejected by banks – a downstream measure influencing total time taken for wage payment delivery – was unaffected, indicating the quality of bureaucrat work did not deteriorate. We also found no change in the frequency of program irregularities reported by external auditors, including financial misappropriation. Finally, our transfer tracking exercise shows an 11 percentage point (23 percent)

[3]In the 2019-20 fiscal year, more than 50 million rural households participated in the program at a cost of approximately US $10 billion. Multiple studies have documented MGNREGS' positive impacts on poor rural households' well-being (Deininger and Liu 2013; Imbert and Papp 2012; Klonner and Oldiges 2014; Muralidharan et al. 2018).

decline in middle manager transfers in districts where the district principal received PayDash.

We exploit experimental variation in the level of the officer hierarchy receiving PayDash to document substitution in payment processing impacts. Providing PayDash to the principal and middle manager results in no greater improvement than offering access to any one level of the hierarchy, demonstrating the direct role of information in helping mid-level bureaucrats address local implementation challenges. If payment delays largely involved middle managers shirking or strategically delaying processing to extract program rents, and PayDash helps the principal monitor middle-level subordinates, we would anticipate complementarity in providing PayDash to the principal and middle managers. In follow-up surveys, a majority of district officers reported sharing management-relevant information from PayDash with their subordinates, consistent with substitutability. PayDash also improves the accuracy of middle managers' assessment of their jurisdiction's payment processing performance at endline.

A comparison of districts that are above- versus below-median in terms of the average number of gram panchayats (GPs) per subdistrict ("high GP ratio" and "low GP ratio", respectively) provides further insight into the channels underlying the impacts of PayDash.[4] Relative to their counterparts in low-GP-ratio districts, middle managers in high-GP-ratio areas are responsible for roughly twice as many local administrative units, score higher on a workload index, and hold significantly less accurate baseline beliefs regarding program performance. Improvements in average payment processing times are concentrated in high-GP-ratio areas, which were worse performing at baseline. Improvements in workfare availability (beneficiary person-days worked and related indicators) and the quality of officer work (payment request rejections) primarily occur in low-GP-ratio areas. This pattern of impacts is consistent with improved information resulting in officials' directing effort towards different dimensions of implementation depending on the information content.

Our research adds to the growing body of evidence that highlights how limited information impacts the inner workings of government administration and the quality of public service delivery (Tirole 1986; Dixit 2002; Finan et al. 2017), even in a digitally-managed system like MGNREGS (Muralidharan et al. 2016; Banerjee et al. 2020; Muralidharan et al. 2021). The existing focus of this literature has largely been on moral hazard, the value of improving top-down monitoring to discipline middle and lower-level officials, and when such efforts may fail.[5] More recent work under-

[4] We discuss the rationale for this approach in Section 6.

[5] For example, the value of top-down monitoring may unravel if incentives of managers and the principal are not aligned (Banerjee et al. 2008) or if the principal is unwilling to enforce penalties (Dhaliwal and Hanna 2017).

scores the importance of information available to middle managers.[6] Dal Bó et al. (2021) show that mid-level supervisors hold information unobservable to higher-level principals that, when leveraged appropriately, can improve service delivery and reduce frontline agent shirking, and Bandiera et al. (2021) find that optimal use of incentives and allocation of authority in bureaucracies depend on the extent to which bureaucrats' preferences at multiple levels align with organizational goals. In our case, reduced information costs, in a context with overloaded bureaucrats, allows middle-level implementers to improve outcomes. Our result is in line with recent studies that point to the value of bureaucrat autonomy (e.g., Bandiera et al. (2021); Rasul and Rogger (2018)), and highlights the value of information provision in achieving public sector aims, even in situations where multitasking concerns envisioned by Holmstrom and Milgrom (1991) are likely quite relevant.

To the best of our knowledge, our study is the first to experimentally vary access to information relevant to service delivery across levels of the bureaucratic hierarchy, providing greater insight into the relative importance at the middle level of the hierarchy of agency concerns as compared to information constraints.[7] A key contribution is to demonstrate the importance of reducing the costs of acquiring information as an input to service delivery in an environment with bureaucratic overwork.[8] The monitoring channel is less relevant in our capacity-constrained context, and the use of high-powered incentives normally thought useful to improving outcomes (transfers of low-performing officers) declines as the information environment improves. In our context, information is relevant both to the bureaucrat herself and as part of cross-level cooperation.[9]

Our results are also consistent with research showing bureaucrats in limited-capacity settings are overworked. For India, (Dasgupta and Kapur 2020) show middle management bureaucrats are

[6]For example, recent research inspired by the work of Bloom and Reenen (2010) on firm management highlights the relevance of middle managers in social security office performance in Italy (Fenizia 2022), and Rasul et al. (2020) identify variation in project completion rates in Ghana based on the management practices of mid-level bureaucrats.

[7]Deserranno et al. (2020) vary financial incentive provision at multiple levels and find effort complementarities. Dal Bó et al. (2021) explore knowledge differences across the hierarchy but do not vary access to information at different levels.

[8]Aman-Rana et al. (2022) highlight another potentially important dimension of underresourcing the bureaucracy that may be relevant in our setting, that of underfunding work civil servants are expected to undertake - a phenomena that could sustain a low-level equilibrium where bureaucrats use personal funds to provide public services, extract rents that, in part, enable them to deliver those services, and underinvest in formal fiscal capacity. While this parallel "informal fiscal system" may be operative in our context, our study focus is instead on underresourcing that manifests as a large scope of responsibility placed on a single bureaucrat.

[9]In this sense, we connect to work exploring the value of mission in aligning incentives across levels, where bureaucrats act as motivated agents that serve the needs of citizens (Besley and Ghatak 2005; Prendergast 2007), and earlier theoretical work that outlines conditions under which contracts can be designed to elicit effort to help a colleague Itoh (1991), or otherwise cooperate, even in a setting with agency concerns, to achieve an organizational objective Itoh (1992). In contrast to Mattsson (2021), we see that information on delays improves our primary outcome of interest - payment timelines - without evidence of increased corruption.

heavily under-resourced relative to their responsibilities, negatively impacting program implementation. Rogger (2017) provides complementary cross-country evidence that bureaucrats in low and middle-income countries commonly work overtime.[10] Our study shows how informational gains within such a bureaucracy translate into gains for citizens in terms of both lower payment delays and, importantly, greater work provision. Payment delays can lower the protective value of G2P payments (Basu and Sen 2015) and reduce citizens' willingness to participate in the program in the first place (Dréze 2020). Given the importance of timely payments to low-income communities and the potential for delays to persist despite digitization, we see this study helping to fill an important gap in the literature related to service delivery.

The paper is organized as follows. Section 2 describes the context, section 3 covers research design, and section 4 describes the data and empirical strategy. Section 5 presents results, section 6 explores potential mechanisms, and section 7 concludes.

2 Context

In each Indian state, a three-tier administrative hierarchy situated within districts implements and monitors MGNREGS activities. Below, we describe the work verification and wage payment process and the officials involved.

2.1 MGNREGS administration

In brief, agents associated with the village governance units – Gram Panchayats (GP) – implement the MGNREGS program, middle managers at the subdistrict level monitor and support work verification and payment processing, and district-level officials are the relevant principal and serve in an overarching monitoring role. This section describes the administrative structure in more detail, and Appendix Figure A1 provides a visual summary.

Stage 1a: GP-initiated steps Frontline agents - both elected and appointed - initiate a MGNREGS worksite and project and offer workdays to interested villagers. On completion of each

[10] Rogger (2017) reports on surveys of nearly 7,000 civil servants that ask about workload in a variety of organizations, departments, and levels across Pakistan, the Philippines and Indonesia. In these surveys, respondents report that, on any given day, 17 percent of their colleagues do not work a full day, while 32 percent of their colleagues work more than a full day, suggesting workload and bandwidth are prevalent issues – and more significant than concerns about shirking – across a variety of contexts.

six-day workspell, a contracted local officer (Gram Rozgar Sevak, now on GRS) enters worker details and attendance in the "muster roll". Alongside, a subdistrict-based engineer visits the worksite to record completed work in the muster roll and her own measurement log. Worker participation and work completed are input into the web-based MGNREGS Management Information System (MIS) by the GRS, often with subdistrict officer support. Central government guidance states these GP-based steps - digitizing muster roll information and work measurement - should occur within two and three days of the conclusion of a workspell, respectively (Ministry of Rural Development, Government of India (2018), Ministry of Rural Development, Government of India (2022)). Delays can occur here, for example, while officials wait for engineers to visit or input details from worksites or when the GRS-initiated data digitization is delayed.

Stage 1b: Subdistrict steps Key middle managers in this context are the Chief Executive Officer (CEO), the highest ranking civil servant overseeing all welfare schemes (including MGNREGS) in the subdistrict, and the Program Officer, (PO) the highest ranking officer solely responsible for MGNREGS oversight in the subdistrict. The PO reports to the CEO.[11] The role of middle managers is, in large part, supervisory and intended as a check on GP-level delays and malfeasance in processing. The PO monitors information submitted by GP agents, and the CEO digitally signs off on funds transfer orders (FTOs) to officially approve wage payments.[12] FTO sign-off completes stage 1 (as officially referred to by the government) of wage payment processing and results in the sending of payment requests to the government's electronic funds management system (the Public Financial Management System, or PFMS).

Subdistrict POs have a relatively hands-on role in MGNREGS – they both directly supervise frontline agents and review their efforts in the process of work verification and processing payments. They routinely visit GPs and, in turn, frontline agents regularly travel to subdistrict offices for coordination purposes. Subdistrict POs also commonly use WhatsApp groups with lower-level officials to stay apprised of MGNREGS-related issues. Subdistrict CEOs, in contrast, divide attention across multiple programs and are generally less involved in day-to-day MGNREGS management.

[11]Official titles used throughout the paper are those used in Madhya Pradesh. In Jharkhand, corresponding bureaucrat titles are Development Commissioner (CEO) and Assistant Program Officer (Program Officer).

[12]Signatures are required by two subdistrict officials. The Subdistrict CEO is one of these two officials in Madhya Pradesh, but not Jharkhand.

Stage 1: District supervision Analogous to subdistrict, the two key district personnel are the District CEO, who has an overarching supervisory role for all welfare schemes within her district, and the District PO, who focuses entirely on MGNREGS and reports to the CEO.[13] District officials have a supervisory role, which includes regularly communicating with mid-level managers via phone calls and WhatsApp/text messaging and conducting periodic in-person meetings to review performance and discuss problems.

Stage 2: Central government and bank steps After the FTO is sent, payment requests are routed via the PFMS to a bank that then disburses payment into workers' bank accounts. The payment transfer sometimes fails to complete, resulting in a "rejected FTO", the large majority of which relate to invalid recipient account, bank, or individual identification (Aadhaar) numbers having been provided, or accounts having been "frozen" due to limited use. A rejected FTO is flagged in the PFMS system for correction by the subdistrict office and re-routing to the bank.

Baseline program performance Our primary focus is on stage 1 of wage processing, which occurs within districts and is mandated by the central government to take a maximum of eight days. Based on data for the universe of 3.1 million muster rolls – covering more than 170 million person-days worked – in our two study states for the year preceding the start of the PayDash intervention (February 2016 through January 2017), the subdistrict-month average processing time was 18 days, with a standard deviation of 12.5 days. Figure 1 shows that more than 85 percent of subdistrict-months fall above the 8-day threshold, with a long right tail to the distribution.[14]

Additional officer responsibilities Beyond their involvement with work verification and payment processing, subdistrict officials additionally play important roles in selecting which potential MGNREGS projects are initiated and publicizing the availability of projects for individuals interested in participating in the program to join (Gulzar et al. 2017). The volume of person days worked under MGNREGS can therefore be influenced by the effort made by these officials in these dimensions. Frequent news and policy reports suggest that work provision by local officials is a key constraint to citizen access to MGNREGS, and that unmet demand for work, perpetuated in part by lack of open worksites, is widespread.[15]

[13] In Jharkhand, the corresponding positions are Development Officer (CEO) and Program Officer.

[14] For readability, both plots trim values above the 99th percentile.

[15] Azim Premji University (2022) report on survey data collected across four states, estimating that 39% of households that wanted to work for MGNREGS during the 2020-21 fiscal year could not access any work at all. Conditional

2.2 Who are MGNREGS personnel?

We next use our baseline survey and government administrative data, the construction of which is described in Section 4.1, to examine characteristics of the middle and upper-level bureaucratic personnel involved in managing MGNREGS and of the administrative units they oversee. Panel A of Table 1 shows that the average district official (CEO or PO) in our study states oversees 7.6 subdistricts, and the average subdistrict official (CEO or PO) is responsible for roughly 50 GPs, with a large amount of variation. Districts in our study states have an average population of roughly 1.4 million, with 78 percent of residents living in rural areas.

We turn to district and subdistrict officer characteristics in Panels B and C, respectively. These officials are typically mid-career (aged early 40s), and predominantly male and college educated. Smartphone ownership is nearly universal (not shown) and more than 90 percent of officers reported that they access online MGNREGS administrative data via the status quo interface at least once a day.

At both levels of the hierarchy, high workloads are pervasive. Across administrative levels, officers report working 70 or more hours per week and making 40 or more work-related calls per day on average. Consistent with bandwidth constraints due to work overload, when asked what the average time taken for MGNREGS worker payment delivery in their jurisdictions was over the previous year, the average absolute deviation between the value given by officers and the actual value as a share of the actual value ("knowledge gap") was 38 percent for district officials and 46 percent for subdistrict officials. In addition, subdistrict officials on average report being in regular weekly contact with local agents in only 36 percent of the GPs under their purview. Finally, 93 percent of district officials themselves indicate that subdistrict officials are overworked (not shown). For use in our subsequent analysis, we generate a "workload" index variable based on the hours worked per week, calls per work days, knowledge gap, and (for subdistrict officials) irregular local agent contact variables.[16]

on working, households would have liked to have accessed 64 more days on average than the work-days provided. At 63%, the most commonly cited constraint to work provision reported by citizens was the lack of sanctioned and open worksites.

[16]Separately by officer type, we calculate z-scores for each component variable and define the index value as the average of the non-missing component z-scores.

2.3 MGNREGS implementation challenges

As part of baseline activities, we conducted semi-structured interviews with more than 75 MGNREGS officials to understand how they accessed information and what challenges they faced in processing payments. Officials reported relying on administrative data available on the central government MGNREGS website to monitor work verification and payment processing, but frequently stated that doing so was very time consuming. To view information on payment processing times, subdistrict officials needed to visit separate webpages for each GP-by-payment-step - in a setting where they manage more than 50 GPs on average and stage 1 is divided into five different steps. The effort required to access, export, and then put this information into a format better suited for officers' needs was generally viewed as not worth regularly incurring, especially given internet connectivity issues and limited staff bandwidth.

Consistent with high mid-level information acquisition costs, when subdistrict POs were asked in the baseline survey to rank MGNREGS-related implementation challenges, the highest average rank went to "infrastructural issues such as poor internet connectivity and power shortages" (Panel A of Figure A2). We also asked the officials to identify the most important challenges faced by MGNREGS participants. Wage payment delays were given the second highest average rank out of seven categories, behind only low program wage rates (Panel B of Figure A2).[17] Finally, regarding performance incentives, 49 percent of district officials and 35 percent of subdstrict officials indicated that they had engaged in transfers of their subordinates based on performance, in line with the importance of posting location as a performance incentive seen in other developing country bureaucracies (Finan et al. 2017; Khan et al. 2019).

3 The PayDash intervention

3.1 The Paydash App

In collaboration with India's central Ministry of Rural Development (MoRD), we developed "PayDash", an Android smartphone and web-based application designed to provide information relevant to monitoring and managing MGNREGS work verification and payment processing in a readily accessible and actionable format. Underlying PayDash are timestamps generated as officials log in to

[17] Payment delays in MGNREGS have long been seen as undermining the protective premise of the program (Basu and Sen 2015; Muralidharan et al. 2018), leading workers to rely on alternative, largely negative, coping strategies and making them vulnerable to exploitation (Dréze 2020).

the MGNREGS MIS and complete work verification and payment processing steps for each muster roll. This information is channeled through web application programming interfaces (APIs) from the MIS to PayDash. These timestamps are automatically generated metadata, allowing us to avoid concerns regarding the accuracy of user-provided information (Muralidharan et al. 2021). Logins are user-specific, so officers receive daily-updated data only for areas under their jurisdiction, and the PayDash mobile app is offline compatible, allowing information from the last time of update to be viewed even in areas with poor internet and mobile connectivity.

PayDash is customized by level of administrative hierarchy, while remaining centered on muster rolls as the basic unit for officer action. The left panel of Appendix Figure A3 shows an example user's home screen for the subdistrict version of PayDash. The daily-updated statistics provided on this screen include the total number of muster rolls delayed across all GPs in the subdistrict, and officers can further click through to different "cards". Each card – a screen corresponding to a specific GP and frontline agent – provides the number of muster rolls delayed at steps for which that individual is responsible, as well as details about each delayed muster roll (right panel of Appendix Figure A3). The user can click an icon on this same card to contact the subordinate directly via a call or WhatsApp message pre-filled with relevant muster roll details. PayDash also includes a performance dashboard providing charts of subdistrict and GP-wise current and historical processing time, both overall and by step (Appendix Figure A4).

The district officer version of PayDash is structured similarly to the subdistrict version, differing primarily in the granularity of information provided. Users have home screens providing statistics at the district level, and their cards correspond to subdistricts. Each card provides the number of muster rolls delayed in total and by step, as well as contact icons for the relevant mid-level official. The performance dashboard is structured identically to that in the subdistrict version, but provides information at the district and subdistrict levels.

3.2 Intervention design

We randomized access to PayDash across the low-income states of Madhya Pradesh and Jharkhand, covering 73 districts and 561 subdistricts.[18] Districts were randomly assigned into the following groups: 17 districts where only district administrators received PayDash ("District Only"); 16 districts where only subdistrict administrators received Paydash ("Subdistrict Only"); 20 dis-

[18]We exclude one pilot district in each state. Official statistics for the 2016-17 fiscal year indicate per capita income in both states of approximately US$2 per day (authors' calculations, available upon request).

tricts where both district and subdistrict administrators received PayDash ("Combination"), and 20 districts forming our control with no Paydash provided.[19] Within each treated level of the administrative hierarchy, PayDash was provided to the CEO and PO.[20]

In each state, we stratified by above/below median values of average muster-roll-by-worker payment time and average per-subdistrict volume of person-days within the April 2015 to June 2016 range.[21] Subdistrict access to PayDash was clustered by district due to the high potential for within-district spillovers – e.g., it is common for district officials to hold regular district-wide video conference meetings with subdistrict officials to discuss MGNREGS performance.

In close coordination with each state's nodal MGNREGS department, we rolled out PayDash across Madhya Pradesh in February and March 2017 and Jharkhand in October 2017.[22] We undertook geographically dispersed training sessions that allowed us to conduct in-person training and baseline surveys with nearly all relevant officials. Overall, 1,293 district and subdistrict CEOs and POs (94 percent of all positions) attended one of 177 in-person training sessions covering MGNREGS administration and, for treatment officers, PayDash. Conditional on being present at a training session, over 99 percent of officers completed a baseline survey. The coverage gap was due primarily to vacant positions at the time of baseline - i.e., the previous officer had vacated the position and the replacement had not yet been posted. Officers unable to attend the initial sessions were later followed up with individually for training and onboarding. Training and survey completion rates are statistically indistinguishable across treatment arms.[23]

Training sessions for control and treated districts were conducted separately, as were sessions for subdistrict and district officials. All officials, regardless of treatment arm, received basic training on existing MGNREGS MIS tools and completed baseline surveys. We provided this basic "refresher" training to ensure that officers across both control and treatment arms knew how to access information from the MGNREGS MIS – in this way, treatment assignment only varied how easily officers could access payment-related information and not whether they knew how to access to that information, or had more knowledge in general of MGNREGS systems. Treated official sessions additionally involved installing the PayDash mobile-phone app and training in how to use

[19] We assigned treatments in approximately equal proportions across Madhya Pradesh's 50 districts. In Jharkhand's 23 districts, we assigned one-third to control and Combination, and one-sixth to District Only and Subdistrict Only.

[20] While we assumed prior to the intervention that POs would be the primary platform users, CEOs were also given access with the aim of increasing bureaucratic buy-in and support for the study.

[21] Appendix Section B.2 provides additional details on these variables.

[22] In the subsequent analysis, all districts in Madhya Pradesh are assigned a February rollout month.

[23] An F-test of the joint hypothesis of zero-valued treatment arm coefficients in a regression of training participation (survey completion) on treatment assignment indicators and randomization strata gives a p-value of 0.634 (0.805).

the platform. The typical PayDash training lasted approximately 45 minutes.[24]

The evaluation period continued through August 2018.[25] Over the course of the evaluation, we contacted each district at multiple points in time to identify any position changes and adjust PayDash access accordingly.[26] Officers newly assigned to treatment areas were provided PayDash access for their region and given in-person or remote training, depending on logistical feasibility. Officers transferred between treated areas had the region-specific information available to them via PayDash updated, while those exiting treated areas entirely had their login access deactivated.

3.3 Conceptual framework

MGNREGS work verification and payment processing occurs within a multi-tiered bureaucratic hierarchy. District officers manage and monitor the performance of subordinate district officials. These subdistrict officers complete the later verification and processing steps themselves and in turn manage and monitor local-level officials, who are responsible for carrying out the earlier steps.

Both district and subdistrict officers must exert costly effort to gather the information necessary to identify delays, determine who to hold accountable, and take action to address problems. We assume that officers may be influenced by factors including extrinsic performance incentives and intrinsic motivation. In this setting, a technology that reduces the costs of information acquisition has the potential to reduce payment processing times when provided at either the district (upper) or subdistrict (middle) level.

First, mid-level officers may have easy access to the information they need to perform their duties well, but be weakly incentivized to make the effort of collecting and acting on that information to improve program performance. In this case, outcomes may be improved by reducing the costs for upper-level officials of acquiring information relevant to monitoring the performance of the mid-level officers. Alternatively, mid-level officials may be strongly incentivized, but face high information acquisition costs that limit the gathering of information they need to implement the program effectively. This suggests the potential of reducing information acquisition costs at the middle level of the hierarchy to achieve improved program performance.

It may also be that both weak incentives and information constraints are relevant at the middle

[24] Additional training session details are provided in Appendix Section B.1.

[25] We concluded the intervention prior to the Madhya Pradesh state assembly elections, which took place in November 2018. In the months immediately prior to elections, district and subdistrict officers can be shifted and deputed to help with election preparation.

[26] States do not centrally maintain regularly updated rosters of district and subdistrict officials' postings.

level of the bureaucratic hierarchy, so that complementarities exist in concurrently reducing information acquisition costs at the upper and middle levels. On the other hand, if mid-level officials are already well incentivized and their superiors understand that they are information-constrained, reducing information acquisition costs for higher-level officials may result in their sharing the new management-relevant information with their subordinates, yielding a substitute relationship in addressing information constraints for officers at the middle and upper levels.

In addition, even if information constraints are broadly relevant across different regions, the impacts of PayDash may differ depending on the content of the information it makes easier to acquire. If, e.g., areas where middle managers oversee a larger number of local administrative units have slower processing times, gains in program performance may be stronger in that dimension in those locations as compared to areas with a higher ratio of middle managers to local agents (and faster processing times). In the latter, better informed officers may shift some effort toward improving other dimensions of program performance.

4 Data and Empirical Strategy

4.1 Data sources

Officer survey data The information collected in our baseline surveys of district and subdistrict CEOs and POs in Jharkhand and Madhya Pradesh included sociodemographic characteristics, work and management practices, and MGNREGS administration. Between May and December of 2020, we conducted a follow-up survey with the set of baseline subdistrict and district POs in Madhya Pradesh. We achieved a coverage rate of 77.1 percent for these 358 officers, with insignificant differences by treatment assignment.[27] These surveys collected additional information on work and management practices, MGNREGS administration, and treated officials' use of PayDash.

PayDash usage data We obtain Google Analytics data on officer usage of PayDash during the intervention period. Using this data, we generate officer-month-level measures of the total number of distinct usage sessions, duration of usage (available only for the mobile application), and number

[27]An F-test of the joint hypothesis of zero-valued treatment arm coefficients in a regression of survey completion on treatment assignment indicators and randomization strata gives a p-value of 0.847. The lower completion rate and single-state focus reflect the challenges of conducting phone-based surveys with officers during the period in which they were heavily involved in managing the government response to COVID-19.

of WhatsApp messages and calls placed from within the mobile application.[28] The total session and mobile duration measures provide lower bounds because the Google Analytics data does not capture user engagement when PayDash is in offline mode.

MGNREGS administrative data We obtained data on payment processing for the universe of approximately 19.5 million muster rolls issued in Jharkhand and Madhya Pradesh between February 2016 and August 2018. For each muster roll, we have information on the GP in which it was issued, the start and end date of the associated workspell, and the date of associated payment request submission by the subdistrict office to the central funds management system, PFMS. These data allow us to determine the total length of time spent on the work verification and payment processing steps for each muster roll before submission to PFMS. We use this information to construct subdistrict-month-level measures of average processing time, an indicator for the average processing time being longer than eight days, the average absolute deviation from the median processing time, the share of muster rolls with processing times exceeding different thresholds, and the total number of muster rolls.

Separate administrative data sources covering the same time period allow us to construct subdistrict-month-level measures of the total person-days worked by MGNREGS participants and the average share of payment requests subsequently rejected at the PFMS stage.[29] We also link data on the characteristics of all MGNREGS participants in our study states - drawn from publicly-available worker identity documentation - to administrative data on their days worked over this same period. Using this data, we construct subdistrict-month measures of the number of working households, number of villages in which these households are based, and average number of days worked per household. We also generate measures of the shares of workers belonging to marginalized groups, specifically females and members of government-identified “Below Poverty Line” households.

External audits data We construct measures of the quality of MGNREGS implementation and incidence of corruption using publicly available data from external program audits conducted by the government. Known as “social audits”, these are GP-level exercises conducted by independent

[28] A distinct usage session is logged when a user interacts with PayDash and at least 30 minutes has passed without activity since the previous session, or when an ongoing session continues into an additional calendar day.

[29] Section 5.3 discusses the PFMS stage in greater detail.

auditors from outside the community to assess the quality of local MGNREGS delivery.[30] We generate an audit-level irregularity index based on indicators for the occurrence of issues in each of the four main categories recorded in official audit reports: financial deviation, financial misappropriation, grievances raised, and other process violations.[31] We additionally create an indicator for unmet community demand for MGNREGS work based on whether auditors record there being "some" or "a lot of" unmet demand (versus "none") in the community based on information gathered during door-to-door visits.[32]

Officer transfers data We tracked officials' posting changes during the intervention period by completing multiple rounds of calls to government offices in each district to determine which officers had been transferred, and to which locations, since the previous calling round. This exercise, which we conducted four times through the intervention period for Madhya Pradesh and three times for Jharkhand (given the shorter intervention duration there), allows us to generate locality-posting level measures of transfer occurrence at different cross sections in time.

4.2 Empirical approach and balance check

Given the experimental setting, our primary specification for analysis using panel data is:

$$Y_{sdt} = \beta_1 TD_{dt} + \beta_2 TS_{dt} + \beta_3 TC_{dt} + \alpha_s + \alpha_t + \theta_{dt} + \varepsilon_{sdt}, \tag{1}$$

where s is a subdistrict in district d in month t, α_s and α_t are subdistrict- and month-level fixed effects, and Y is an outcome of interest. TD, TS, and TC are indicator variables for whether subdistrict s falls in a district with access to District Only PayDash, Subdistrict Only PayDash, or Combination PayDash, respectively. Also included are controls for district-specific linear time trends, θ_{dt}, to adjust for any chance occurrence of differential pre-trends. Standard errors are clustered by district. We also estimate specifications with the treatment-arm-specific indicators replaced by an indicator for any PayDash provision.[33] We use this design to evaluate the impacts of district- and subdistrict-level provision of PayDash, as well as to test for complementarity or

[30] Appendix B.3 provides more information on social audit procedures.

[31] The index is constructed as the average of z-scores generated for each component, normalizing based on the control group mean and standard deviation.

[32] In response to the question: "Is there a demand for work that is not met?"

[33] Appendix Table A4 presents the results of the corresponding synthetic difference-in-differences approach (Arkhangelsky et al. 2021).

substitutability between them (against $H_0 : \beta_3 = \beta_1 + \beta_2$).

To examine the evolution of PayDash impacts over time, we use the following specification:

$$Y_{sdt} = \sum_{\substack{-6 \leq \tau \leq 9, \\ \tau \neq -1}} [\beta_{1,\tau} TD_{\tau,dt} + \beta_{2,\tau} TS_{\tau,dt} + \beta_{3,\tau} TC_{\tau,dt}] + \alpha_s + \alpha_t + \theta_{dt} + \varepsilon_{sdt}, \tag{2}$$

where $TD_{\tau,dt}$ is an indicator variable for whether month t in district d falls τ months relative to District Only PayDash provision. The month prior to PayDash provision ($\tau = -1$) is omitted as a normalization, $\tau = -6$ captures all periods six or more months prior to rollout, and $\tau = 9$ captures all periods nine or more months after rollout. $TS_{\tau,dt}$ and $TC_{\tau,dt}$ are analogous relative-period-specific indicators for Subdistrict Only and Combination PayDash provision, respectively.[34]

To examine potential heterogeneity in the effects of PayDash by districts' administrative structure, we use specifications analogous to equations (1) and (2) that allow the impacts of each treatment arm to vary by whether a district has an above- or below-median average number of GPs per subdistrict. We also consider a more flexible specification where we allow treatment effects to differ by sextile of the average-GPs-per-subdistrict distribution.

In Panel A of Table 1, we test for balance across a set of district-level program and administrative characteristics. In addition to average muster roll processing time and average absolute deviation from the median, we consider total person-days worked, total muster rolls, and the average share of payment requests rejected, defined over the year prior to the launch of the PayDash intervention (February 2016 through January 2017). We also consider variables related to district administrative structure (number of subdistricts and average number of GPs per subdistrict) and composition (total population and share rural, as reported in the 2011 Indian census).[35] In Panels B and C, we consider baseline sociodemographic and work-related characteristics of the district and subdistrict officers responsible for managing MGNREGS. Column (1) reports the mean and standard deviation of each variable for control districts, and columns (2) through (4) present coefficients and standard errors from regressions of each variable on PayDash treatment arm indicators (with control as the omitted category), controlling for randomization strata.[36] Column (5) reports the p-values from tests of the joint hypothesis of zero-valued treatment arm coefficients. In none of the panels do we

[34] Appendix Figure A9 shows results of using the corresponding interacted weighted estimator (Sun and Abraham 2021).

[35] Appendix Table A1 further considers the monthly average number of working households, number of working villages, and average number of days worked per household.

[36] In Panels B and C, the regressions additionally include a program officer indicator.

observe systematic pre-intervention differences by treatment arm.[37]

5 The Impact of PayDash Provision

Before examining the impact of PayDash on our four domains of interest – payments, work provision, work quality and corruption, and transfers – we examine the extent to which officers made use of PayDash, by officer type, level and treatment arm.

5.1 Did officers use PayDash?

We first examine officer engagement with PayDash. Table 2 presents usage statistics for district officers in Panel A and subdistrict officers in Panel B.[38] Observations are defined at the locality-month level for each officer type, spanning the set of intervention months in the two experimental states. Within each panel, the means and standard deviations of monthly usage are presented separately for CEOs and POs and, for each officer type, we further split between localities where only one level of the hierarchy received PayDash and those where both levels were provided access. As mentioned before, our data provides lower bounds on usage because it does not capture when officers use PayDash in offline mode.

Columns (1) and (3) show that average usage is similar for district and subdistrict POs, at roughly 3.7 total sessions and 20 minutes of mobile-based engagement per month. In contrast, as shown in columns (2) and (4), district CEOs average less than one session and three minutes per month, with subdistrict CEOs slightly higher than their district counterparts, at 1.5 sessions and five minutes per month on average. The greater PayDash engagement observed for POs at each level is unsurprising since POs are solely tasked with the management of MGNREGS, while CEOs have a wider variety of responsibilities. In addition, breaking the number of PayDash sessions out by interface type (not shown), fewer than five percent of sessions for each of the four officer types occur through the web-based interface, suggesting some value to officers of the mobile-tailored presentation and offline availability of information in the PayDash Android application.

In columns (5) and (6), we consider the number of calls made and WhatsApp messages sent to subordinate officials using the in-app contact feature. Use of this functionality is concentrated

[37] Of 93 pairwise differences considered in Tables 1 and A1, 5 are significant at the 5 percent level and 13 at the 10 percent level. Out of 31 joint tests, the null is rejected once at the 10 percent level.

[38] Appendix Figure A6 presents position-wise plots of usage over time.

among district POs, likely reflecting in part that a greater share of their supervision of and information sharing with subdistrict subordinates occurs remotely as compared to subdistrict officials in relation to their GP-level subordinates.

We next use the random variation in which levels of the bureaucracy in each district receive PayDash to determine whether officers' engagement with the platform at a given level is influenced by access at the other level of the bureaucratic hierarchy. For each officer position, Table 2 also reports the results of regressions of usage on an indicator for PayDash provision at both levels of the officer hierarchy, plus month and strata fixed effects. The usage differences for district CEOs and subdistrict officials across treatment arms are small in magnitude. While noisily estimated, the odd-numbered columns in Panel A suggest District POs use PayDash less when their subdistrict officials also have access to PayDash. Such declines are consistent with a setting where district POs share information from PayDash with subdistrict officials, a practice that diminishes when those subordinates have PayDash access themselves. Section 6.2 discusses additional evidence related to the possibility of information sharing across officer levels.

5.2 Did PayDash impact program performance?

A first set of outcome variables focuses on payment performance, including worker wage processing time and variability, as well as broader measures of MGNREGS service delivery such as work undertaken by rural households. We initially focus on impacts on these dimensions when the District Only, Subdistrict Only, and Combination PayDash treatment arms are combined into the "Any PayDash" category and then consider impacts of the different treatment arms in relation to one another.

Column (1) of Table 3 shows that PayDash access reduces muster roll processing times by an average of 1.4 days, or 11 percent of the control pre-intervention mean. We consider the dynamics of the effects of PayDash on average processing speed in Figure 2, which plots the relative-month-specific estimated coefficients and 95 percent confidence intervals for the pooled Any PayDash treatment, based on the corresponding version of estimating equation (2). Reductions in processing time emerge a few months after the start of the intervention and persist throughout the evaluation period.[39]

Maintaining an average processing time below the eight day maximum mandated by the gov-

[39]Similar dynamics are observed in Appendix Figure A8 when each PayDash treatment arm is considered separately and for the other outcomes examined in this section.

ernment is a key performance metric by which subdistrict officers are evaluated. We next examine the impact of PayDash on the likelihood that work verification and payment processing are on average completed "late", i.e., after more than eight days, in a given subdistrict-month. Column (3) of Table 3 shows a 7.1 percentage point reduction in this probability.

To better understand what underlies these improvements in processing performance - e.g., are gains achieved through reductions only in severe delays versus quicker processing more broadly? - we consider the share of muster rolls in each subdistrict-month with processing times above different thresholds ranging between four and 56 days (corresponding roughly to the 10th and 95th percentiles of the distribution of processing times in the year prior to the intervention). Figure 3 shows that PayDash leads to a general leftward shift in the distribution of processing times, with reductions in the share of muster rolls exceeding each threshold up through 32 days.[40] In addition, as both the average and variability of processing times are relevant to MGNREGS' protective value for low-income rural households, we examine in column (5) of Table 3 the impacts of PayDash on the average absolute deviation from the subdistrict-month median. We find a reduction in variability of 0.52 days (8 percent).

The final two columns of Table 3 consider the log of person-days worked by MGNREGS participants, which is a function of both officer effort and worker demand to participate in the program. Column (7) shows that PayDash provision results in an average 19 percent (17.2 log point) increase in person-days worked, in a context where more than 170 million workdays were completed in our experimental states over the year prior to the start of the intervention.[41]

Using additional administrative data, we can decompose the observed impacts on the volume of MGNREGS work completed by program beneficiaries to better understand the nature of increased work activities. Column (1) of Table 4 shows an increase in the average monthly person-days completed per household participating in MGNREGS. We also see in columns (3) and (5) higher numbers of participating households and villages with ongoing MGNREGS work, though these impacts are statistically insignificant and so provide only suggestive evidence of greater program reach.[42] Finally, we consider how the increase in program scale manifests in muster roll processing, with column (7) showing an increase in the number of muster rolls being generated and subsequently

[40] Appendix Figure A7 presents the estimated effects separately by treatment arm.

[41] This translates into approximately USD 79 million in additional funds distributed to low-income households over one year, based on applying the average study area post-treatment daily wage of Rs 167 and the 2017 yearly average exchange rate of 65 INR to 1 USD given here.

[42] Appendix Table A2 shows that PayDash increases the share of workers in the below poverty line category by 0.3 percentage points (2 percent), with no impact on the share female.

processed. Section 5.5 discusses additional evidence relevant to understanding the extent to which these impacts reflect changes in bureaucratic effort versus worker demand. In sum, PayDash not only improves work verification and payment processing times but also increases MGNREGS participation.

We next consider how impacts varied by whether PayDash was randomly assigned to one or multiple levels of the bureaucratic hierarchy. For both payment processing and work volume, Table 3 provides evidence of substitutability in providing the platform at the district and subdistrict levels, with the impact of providing PayDash to both district and subdistrict officers (β_3) significantly smaller than the sum of the district only (β_1) and subdistrict only (β_2) impacts.

Interpreted through our conceptual framework, this pattern of impacts - generally insignificant differences observed across treatment arms, together with the substitutability between district and subdistrict PayDash - first suggests that the gains from PayDash are not driven entirely by strengthening the performance incentives of subdistrict officers via improved district-level monitoring. If this were the case, we would not expect providing PayDash to subdistrict officers alone, which leaves the monitoring technology of district officers unchanged, to yield improvements in program performance. Information constraints at both the upper and middle levels of the bureaucratic hierarchy therefore appear relevant in this context. Second, these results are consistent with treated district officers sharing information with block officials, leading to redundancy when both levels are treated in at least some of the information gains from possessing PayDash directly. In Section 6, we provide additional evidence in support of these two channels.

5.3 Did PayDash influence officer work quality?

PayDash significantly reduced wage payment processing time while increasing the volume of benefits delivered through MGNREGS, but these improvements could come at the expense of bureaucrat work quality. We consider this quality as it relates to payments along two dimensions: processing payments correctly (rather than simply more quickly), and not extracting rents while processing payments. By increasing pressure on officials to reduce processing times, PayDash could worsen the quality of data officers upload as they rush or direct attention away from data accuracy toward pushing data through the system. In addition, by making it easier for subdistrict officers to monitor local activities or by relieving bandwidth constraints that free up time, PayDash could increase the ability of these officials to extract rents from lower-level officials or workers in exchange for completing the later steps of payment processing, influencing the nature of corruption.

As a first measure of officer work quality, we consider the probability that worker payment requests are subsequently rejected. Following the completion of the Stage 1 steps for a muster roll, the subdistrict office submits a funds transfer request to the central Public Financial Management System (PFMS), at which point the payment is either accepted or rejected. At this stage, the most common reasons a payment is not accepted relate to invalid recipient account, bank, or individual identification (Aadhaar) numbers having been entered. These details may be "invalid" due to data entry mistakes by local bureaucrats; workers providing incorrect information; bank accounts being dormant, closed, or frozen; or errors in the link between Aadhaar and bank accounts. In these cases, the payment is "rejected", and the subdistrict office can attempt to address the issue and re-submit the payment request.

In practice, gathering necessary information to address rejections is time consuming, requiring coordination with local-level officials and potentially leading to additional delays in payment delivery or failure to correct the reason for rejection at all. If GP or subdistrict officials are less careful in gathering, entering, or verifying such details in areas with access to PayDash, downstream payment request rejection rates could increase. Alternatively, if PayDash frees up more time for officers to work on such issues or makes it easier to monitor and coordinate with subordinates collecting the relevant details, rejection rates may decrease.

At the PFMS stage, payment requests for multiple muster rolls are typically combined into a single "wagelist". We are able to observe the share of individual-level payment requests rejected for each wagelist and therefore average the rejection rate across wagelists in each subdistrict-month. Using the same panel empirical approach as above, we find no evidence of a negative quality impact as captured by payment request rejection. Columns (1) and (2) of Table 5 show rather that providing PayDash access to officers if anything reduces the average share of payment requests rejected.

Our second measure of quality derives from independently-implemented, local-level audits of MGNREGS. These "social audits" are conducted over the course of approximately a week in each GP and are assigned on a rotating basis. Audits assess the quality of program implementation, output, and record keeping. Officially submitted audit reports provide information about and potentially identify irregularities in multiple dimensions of MGNREGS. Approximately 75 percent of GPs in our experimental sample experienced an audit during our analysis period, with no GP being audited more than once and the likelihood of audit balanced across treatment arms.[43]

Our outcome of interest is the irregularity index based on the occurrence of issues in each of the four main categories considered in official audit reports: financial deviation (typically linked to poor record keeping; reported in 12 percent of control locations), financial misappropriation (including bribes, paying ghost workers, or other evidence of graft; reported in 10 percent of control areas), grievances raised (related to access to work, wages, etc.; reported in 14 percent of control areas), and other process violations (reported in 19 percent of control locations). This aggregate measure therefore captures dimensions of both work quality and potential corruption.

The reference periods for audits in nearly all (94 percent) GPs occurred partially or entirely after the start of the PayDash intervention. We thus restrict our analysis to these audits in the treatment period, regressing the audit irregularity index on district-level treatment indicators and strata fixed effects. Standard errors are clustered at the district level. Columns (3) and (4) of Table 5 show no evidence of PayDash affecting audit outcomes. In Appendix Table A5, we consider each of the four index components separately and see no effects on any dimension of irregularity. Overall, these results demonstrate that providing PayDash access to MGNREGS officials did not result in deterioration of their work quality or increases in fraud as captured by payment request rejections and the external audit process.

5.4 Did PayDash affect use of incentives? – Officer transfers

In bureaucratic systems where the use of financial incentives is often circumscribed, allocation to specific postings may be used as either punishment or reward (Khan et al. 2019). Such transfers can be both costly to implement and serve as a blunt tool for attempting to improve overall performance. In this section, we examine whether access to PayDash influences the probability that subdistrict officials are transferred, relying on novel data we collected via calling rounds to district offices.

Transfers are common in our study context, with 45 percent of subdistrict officers in control areas having been transferred within six months of intervention roll-out in each state.[44] In the first two columns of Table 6, we examine whether PayDash affected the likelihood that subdistrict officers were transferred within this time range. The underlying regressions are at the subdistrict-position level and include treatment indicators together with strata fixed effects and a program

[43] An F-test of the joint hypothesis of zero-valued treatment arm coefficients in a GP-level regression of audit occurrence on treatment assignment and randomization strata gives a p-value of 0.713.

[44] These transfers are nearly always within district.

officer indicator. Standard errors are clustered at the district level. Column (2) shows that providing PayDash to district officers alone reduced the probability of transfer at the subdistrict level by 10.6 percentage points (23.7 percent), statistically indistinguishable from and similar in magnitude to the effect when both district and subdistrict officials receive PayDash.[45] In contrast, the estimated impact of only subdistrict officials receiving platform access is small in magnitude, positive, and statistically distinguishable from the other two treatment arms.[46] Extending the range of consideration to 17 months – the maximum available in our data, and only for Madhya Pradesh due to its earlier PayDash rollout month – we see a similar pattern in Table A3, with PayDash reducing subdistrict officer transfers only when district officers are among those given access.

The reduced movement of subdistrict officers in areas where district officials receive PayDash is consistent with some combination of district supervisors becoming more informed about subordinate performance and responding to treatment-driven changes in that performance. The fact that the MGNREGS performance improvements shown in Section 5.2 are present for the Subdistrict Only treatment arm while transfer impacts are absent, however, indicates that the effects on transfers from district-level PayDash are at least partially driven by changes in district officials' informedness. Regardless of the relative importance of the underlying channels, inasmuch as transfers are a costly tool to manage subordinates, the results in this section suggest that reducing principals' information costs could have important implications for broader bureaucratic efficiency.

5.5 Community demand for MGNREGS

As noted above, the volume of person-days worked in MGNREGS is a function of bureaucrat effort and community demand. We expect the PayDash-driven increase in work volume shown in Section 5.2 to be accompanied by reductions in unmet community demand, unless improvements in the quality of MGNREGS implementation such as quicker payment processing increase the desirability of participation in the program from the perspective of rural households enough to lead to a net increase in demand.

We test whether PayDash influenced unmet community demand for MGNREGS work using information from the external audits, where auditors report whether they observed "some" or "a lot of" unmet demand (versus "none") based on responses given during door-to-door visits to households in each GP. To assess the effects of PayDash, we regress an indicator for unmet

[45] p-value = 0.505

[46] Comparisons to District Only PayDash and Combination PayDash have p-values of 0.012 and 0.060, respectively.

community work demand on treatment indicators and strata fixed effects. Standard errors are clustered at the district level. The final two columns of Table 6 show a significant 12.4 percentage point (42 percent) increase in the likelihood of unmet community demand for MGNREGS work, as captured by the external audit procedure, in areas with PayDash. Given that it occurs together with an increase in work provision, the heightened unmet community demand suggests that improving MGNREGS performance increased citizen interest in program participation.[47]

6 Understanding mechanisms

Improved access to information on payment processing could affect payment processing times, work provision, and management practices through a variety of channels. In this section, we explore which avenues appear most relevant to PayDash impacts.

6.1 Impacts of PayDash on officer knowledge

We first consider whether PayDash resulted in officers being better informed about wage payment processing in their localities. It is possible, for example, that access to PayDash allows officials to reduce time spent gathering an unchanged amount of information, in which case knowledge levels would not improve. Alternatively, the reduced costs of gathering management-relevant information, together with officers' chosen effort levels, may lead them to become better informed.

As a proxy for general officer informedness, we use our follow-up survey data to generate a "knowledge gap" measure analogous to that defined in Section 2.2.[48] We then regress this measure for subdistrict POs on treatment indicators and strata fixed effects, clustering standard errors at the district level.[49] Columns (5) and (6) of Table 6 show that PayDash improves the accuracy of officers' responses, reducing the knowledge gap by roughly 7.8 percentage points (19 percent), with effects across treatment arms that are similar in magnitude and statistically indistinguishable.

In addition, we observe suggestive evidence of substitutability in the impacts of district and subdistrict PayDash on subdistrict officer knowledge.[50] Together with the earlier identified substi-

[47] We do not expect PayDash to affect the external auditors' process of registering citizen demand.

[48] The reference period here is the most recent fiscal year prior to the survey.

[49] We cannot feasibly test for effects with district POs due to the earlier described sample size limitations for the endline survey.

[50] The p-value when testing $H_0 : \beta_1 + \beta_2 = \beta_3$ is 0.192. While this null hypothesis cannot be rejected at traditional levels, we have a relatively small sample size and can reject at the 10 percent level with a one-sided test in the direction of substitutability ($H_a : \beta_1 + \beta_2 < \beta_3$).

tutability in impacts on MGNREGS program performance, this finding is consistent with a setting where district officials share management-relevant information from PayDash with their subdistrict subordinates. These results could, however, also reflect that subdistrict officers' knowledge improves under district-level PayDash access because strengthened monitoring leads them to increase their information gathering effort, ultimately improving program performance. In the next section, we examine officers' self-reports on how they used PayDash to consider these possibilities.

6.2 Officer self-reports on PayDash usage

Our pre-intervention interviews with officers and analysis of baseline surveys suggest that while officers are generally highly educated and technologically proficient, their time is scarce and they balance multiple, competing priorities. Our follow-up surveys with district and subdistrict POs in Madhya Pradesh provide additional evidence suggesting that an important channel of PayDash influence is the provision of information in a readily-accessible and actionable format to users, who also share this information with their subordinates involved in completing work verification and payment processing.

As shown in Figure 4, 81 percent of district officials and 60 percent of subdistrict officials who received PayDash report that the platform made it easier for them to acquire information about MGNREGS wage payment processing in their jurisdictions. In addition, 19 percent of district officers and 27 percent of subdistrict officials indicate that PayDash allowed them to acquire information they did not previously have.[51] While, as discussed previously, officers can technically generate the information provided in PayDash using data available through government websites, accessing and processing this data so it would be useful for day-to-day decision making is a more time intensive process that may be practically infeasible to do regularly. Beyond easing information constraints, PayDash was reported to function as a reminder to pay more attention to wage payment processing by 31 percent of district officials and 46 percent of subdistrict officials.

When asked how they used the information from PayDash, 68 percent of district officers and 63 percent of subdistrict officials report sharing it with subordinates working on MGNREGS within their jurisdictions. Reports of using PayDash to evaluate the performance of subordinates are less frequent, though not uncommon, with 25 percent of district officials and 40 percent of subdistrict officers indicating that they did so. Overall, these results show that, from the perspective of users

[51] 94 (75) percent of district (subdistrict) POs answered affirmatively to either information-related question.

themselves, PayDash made it easier to acquire management-relevant information, which was both shared with and used to monitor subordinate officials.

6.3 Do the impacts of PayDash vary with administrative structure?

Constraints on bureaucrats' time may differ meaningfully based on the administrative structure within which they operate, potentially influencing both initial MGNREGS performance and the impacts of PayDash. Our study context has a large amount of variation in the number of GPs overseen by subdistrict officials, with less so in the number of subdistricts per district.[52] While having a larger number of GP-level subordinates has the potential benefit of providing subdistrict officers with greater manpower with which to complete a given amount of work, it could also worsen their bandwidth constraints to gathering management-relevant information and monitoring subordinates more generally. As a result, the relationship of the GP-to-subdistrict ratio to baseline program performance and the value of providing PayDash to MGNREGS officials is ambiguous.

Given the district-level treatment assignment and our particular interest in officials at the middle level of the administrative hierarchy, we focus primarily on comparisons of the impacts of PayDash between districts with above- versus below-median average numbers of GPs per subdistrict ("high GP ratio" and "low GP ratio" hereafter). While high-GP-ratio districts have an average of 79.5 GPs per subdistrict, as compared to 32 in low-GP-ratio districts, these district types do not differ significantly in terms of number of subdistricts, total population, or rural population share (not shown). They can therefore be viewed as similar in terms of upper-level administrative structure and local-level scale, while plausibly differing meaningfully in terms of mid-level administrative workload. We next examine how the impacts of PayDash on MGNREGS performance vary between high- and low-GP-ratio districts, and we then consider the relationship between administrative structure and baseline officer workload.

Table 7 presents the results of analysis where treatment effects are allowed to differ between high- and low-GP-ratio districts. Columns (1) and (2) show that providing PayDash access leads to a small but significant 0.7 day reduction in average processing times in low-GP-ratio districts. In contrast, we observe larger drops in average processing time (roughly 2.6 days) in high-GP-

[52]The means (standard deviations) of GP per subdistrict and subdistricts per district are 39.4 (27.9) and 7.7 (4.0), respectively. Our review of administrative documents indicates that subdistricts as entities were established in the 1950s and their boundaries have rarely changed through the years. New GPs may be established when current local populations exceed state-specific population guidance, though no such changes occurred during our intervention period.

ratio districts, with similar impacts across the three PayDash treatment arms. A comparison of the pre-intervention mean processing times shows that high-GP-ratio districts (16.8 days) were in general slower to begin with than low-GP-ratio districts (12.2 days). Appendix Figure A10, where we allow for heterogeneity in the effects of PayDash by sextile of the average-GPs-per-subdistrict distribution, shows a general strengthening in impact as the average GP-to-subdistrict ratio increases. In addition, columns (3) through (6) of Table 7 show that the reductions in the probability of processing being "late" on average and in variability are similarly concentrated in high-GP-ratio districts.[53]

While low-GP-ratio districts experience smaller processing time improvements from PayDash, they benefit more strongly in terms of volume of worker benefits delivered (columns (7) and (8) of Table 7) and quality of bureaucrat work (columns (1) and (2) of Table A7). As before, for both processing time and beneficiary work volume outcomes, we also see in Table 7 consistent evidence of substitutability of district and subdistrict PayDash in the areas where the effects are concentrated in the first place.

To better understand the relevance of administrative structure to initial program performance and PayDash impacts, we examine in Table 8 whether subdistrict POs' administrative burden in high-GP-ratio districts tends to be larger, as captured by our workload index variable.[54] In column (1), we observe a strong positive relationship between workload and being based in a high-GP-ratio district. The positive association holds in column (2) when we consider instead the average number of GPs per subdistrict. We consider district POs in columns (3) and (4) and do not see evidence of increased workload in areas where the number of subdistricts under their purview is larger, potentially reflecting the lower variability in the number of subdistricts per district.

Overall, we see that in districts where subdistricts are composed of a larger number of local administrative units, payment processing times are slower and subdistrict program officers experience higher workloads on average. Together with evidence that PayDash results in information gains for officers regardless of administrative structure (columns (7) and (8) of Appendix Table A7), these findings suggest that differences in the content of the information gained influence the nature of subsequent impacts on MGNREGS performance. In high-GP-ratio districts, PayDash leads to

[53]Appendix Figure A11 shows that the PayDash-driven reductions in shares of muster rolls exceeding each of the earlier considered processing time thresholds are also driven primarily by changes in high-GP-ratio districts.

[54]We regress a subdistrict-PO-level workload measure on a district-level high-GP-ratio indicator, a district-level indicator for above-median number of subdistricts, and a state fixed effect, clustering standard errors at the district level. Appendix Table A9 separately considers each of the underlying components of the workload index.

faster work verification and payment processing, while in low-GP-ratio districts officers with PayDash may be shifting some bandwidth to increasing the scale of the program and improving the quality of bureaucrat work.

7 Conclusion

Our field experiment, conducted at scale across two Indian states, involved the full populations of MGNREGS bureaucrats at senior and middle levels of the administrative hierarchy. We randomly assigned access to PayDash, a mobile- and web-based platform that allowed users to more easily manage and monitor the processing of wage payments for the world's largest workfare program. The platform lowered the costs of accessing information about the status of work verification and wage payment processing and helped supervisors more easily identify subordinate officials who needed to take action to address pending steps. We also randomly varied the level of the administrative hierarchy that received access to the e-platform to better understand how information is used and flows through the hierarchy.

Provision of PayDash led to improvements in payment processing times and the volume of program benefits delivered, whether made available at the district or subdistrict level. We see strong evidence of substitutability of district and subdistrict PayDash access in impacts on payment processing times and work volume, and a variety of evidence suggesting that this substitutability relates at least in part to upper-level officers sharing information from PayDash to help their subordinates, rather than using it simply to better monitor their performance. These gains in program performance were not accompanied by deterioration in an important measure of officer work quality – payment rejections – or by higher corruption as captured by independent government audits. Access to PayDash also reduced the occurrence of a costly form of officer performance management, the reallocation of subordinate officials across jurisdictions.

PayDash did not specifically provide new information to officers, but instead packaged information in a more readily-accessible format. Our results, therefore, highlight how seemingly small costs of information acquisition for bureaucrats who administer public programs can be an important constraint to the quality of service delivery in low-income settings. The significant improvements achieved by reducing information access costs manifested in an environment that was already largely digitized, suggesting information constraints are not necessarily resolved simply through technological advancements in G2P payments. Our findings also suggest the broader potential of deploying add-on digital tools in safety net programs, now widespread in lower-capacity bureaucratic settings, to reduce information constraints and achieve meaningful improvements in program implementation.

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Figures and Tables

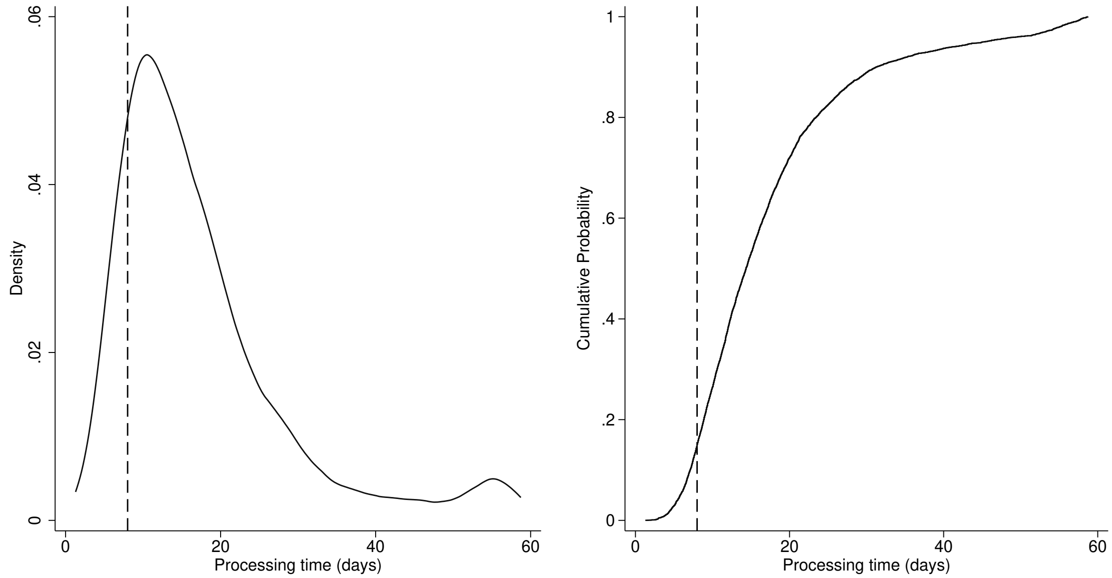


Figure 1: Payroll processing times prior to intervention

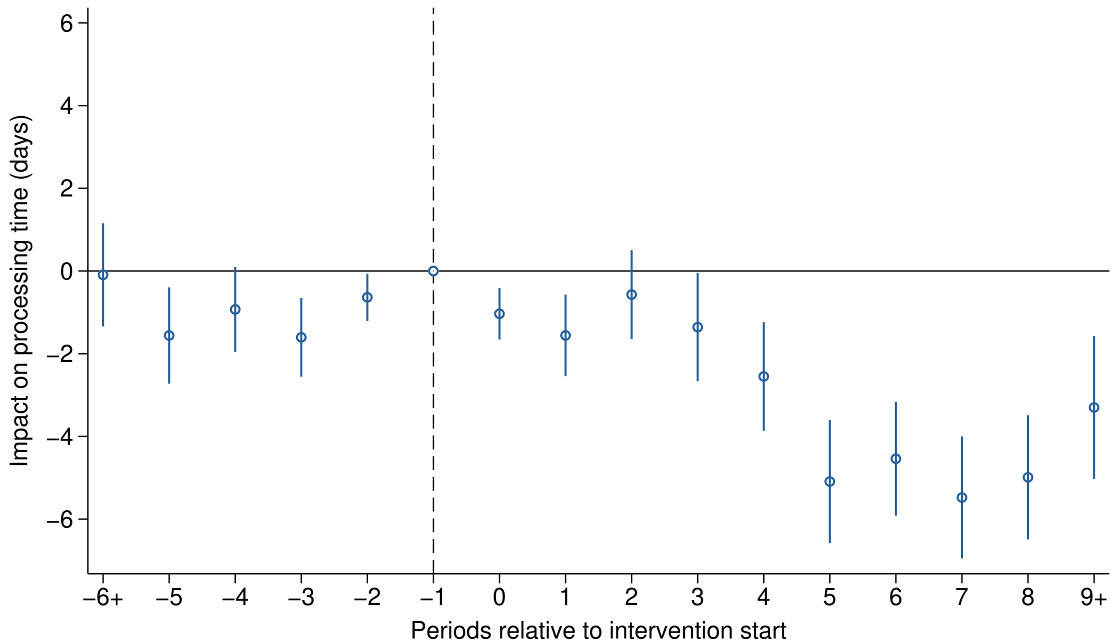


Figure 2: Dynamics of PayDash impacts on processing time

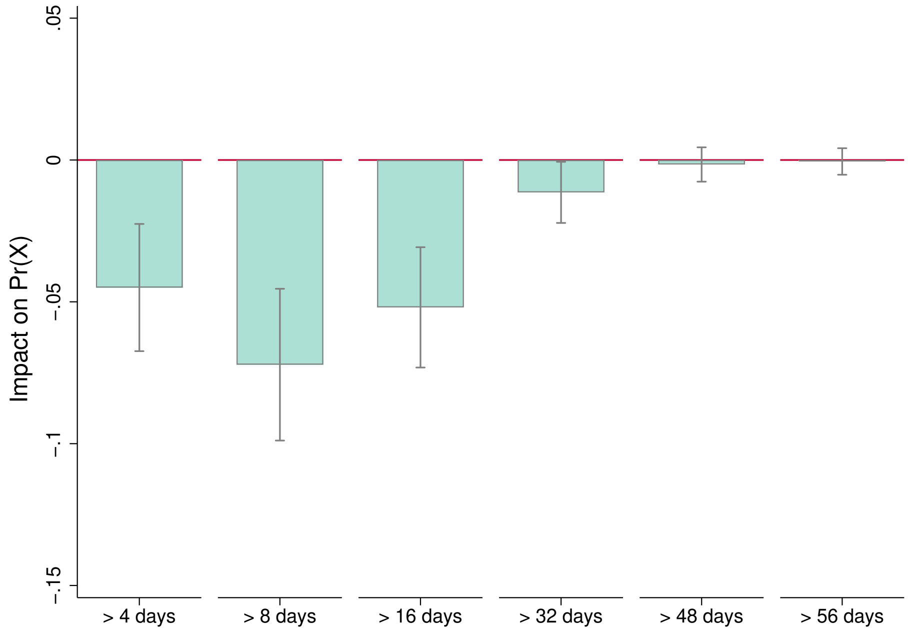
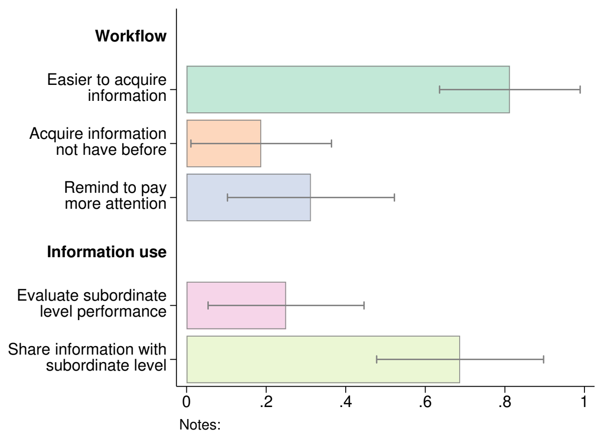
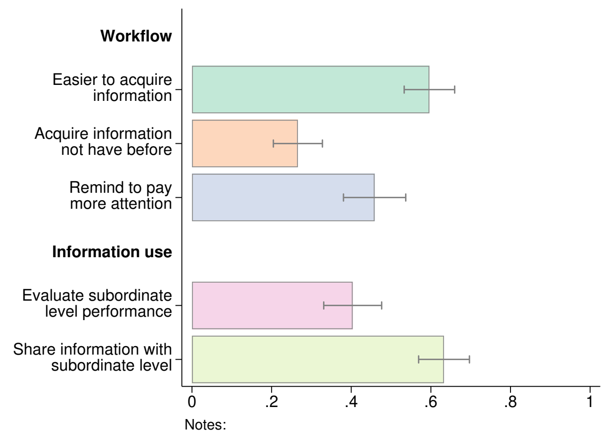


Figure 3: Impacts of PayDash on exceeding processing time thresholds



(a) District POs



(b) Subdistrict POs

Figure 4: PayDash mechanisms of impact - bureaucrat self-reports

Table 1: Baseline characteristics

	Control Mean	District Only	Subdistrict Only	Combination	Joint p-value	Obs
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Program and district characteristics						
Processing time (days)	19.06	-1.56	0.36	-0.82	0.598	73
	[8.16]	(1.60)	(1.45)	(1.43)		
Absolute deviation (days)	10.39	-0.64	0.40	-0.14	0.648	73
	[3.87]	(0.77)	(0.79)	(0.72)		
Person-days worked (x1,000)	2158.86	796.02*	-77.33	395.44	0.203	73
	[1019.04]	(458.71)	(321.18)	(385.10)		
Muster rolls (x1,000)	42.05	12.71	-3.82	2.02	0.493	73
	[30.73]	(11.12)	(7.13)	(7.83)		
Share of payment requests rejected	0.08	-0.00	0.01	0.02*	0.239	73
	[0.03]	(0.01)	(0.01)	(0.01)		
Subdistricts	7.55	1.18	-0.57	0.53	0.335	73
	[4.01]	(1.09)	(0.82)	(1.13)		
GPs per subdistrict	51.32	-0.22	7.57*	3.71	0.228	73
	[25.37]	(4.57)	(3.89)	(3.13)		
Total population (x1,000)	1489.04	-202.12	-141.76	-47.11	0.847	73
	[776.73]	(259.58)	(220.10)	(227.85)		
Rural population share	78.09	2.90	-0.22	-2.66	0.673	73
	[18.92]	(4.93)	(5.46)	(5.14)		
Panel B: District officer characteristics						
Age (years)	43.03	-1.29	-0.72	-1.71	0.883	129
	[9.58]	(2.76)	(2.16)	(2.17)		
Female	0.25	-0.09	-0.16*	-0.12	0.323	132
	[0.44]	(0.11)	(0.09)	(0.11)		
Postgraduate completion	0.89	-0.03	0.02	-0.18**	0.130	134
	[0.32]	(0.08)	(0.08)	(0.09)		
Online data access daily	0.89	0.11	0.11	0.06	0.398	68
	[0.32]	(0.07)	(0.07)	(0.09)		
Workload index	0.06	-0.11	0.02	-0.17	0.515	135
	[0.68]	(0.15)	(0.16)	(0.14)		
Hours worked per week	69.71	1.01	2.93	3.12	0.817	128
	[15.58]	(4.04)	(3.83)	(3.89)		
Calls per work day	38.79	0.39	7.36	-3.97	0.423	123
	[22.26]	(5.29)	(6.79)	(4.73)		
Additional charge	0.53	-0.06	-0.13	-0.16	0.544	118
	[0.51]	(0.15)	(0.13)	(0.11)		
Knowledge gap	0.52	-0.21*	-0.17	-0.22*	0.219	122
	[0.55]	(0.10)	(0.11)	(0.11)		
Panel C: Subdistrict officer characteristics						
Age (years)	40.61	0.77	0.18	0.80	0.410	1009
	[7.57]	(0.65)	(0.69)	(0.53)		
Female	0.18	-0.03	-0.01	-0.03	0.794	1005
	[0.38]	(0.04)	(0.04)	(0.04)		
Postgraduate completion	0.80	-0.05	-0.06*	-0.01	0.156	1011
	[0.40]	(0.04)	(0.03)	(0.04)		
Online data access daily	0.92	0.04*	0.02	-0.02	0.053	987
	[0.27]	(0.02)	(0.02)	(0.02)		
Workload index	-0.05	0.06	0.07	0.04	0.619	1023
	[0.50]	(0.05)	(0.06)	(0.06)		
Hours worked per week	77.43	1.98	4.48**	1.74	0.216	978
	[17.61]	(1.82)	(2.10)	(2.01)		
Calls per work day	45.15	1.62	0.13	3.09	0.606	994
	[25.89]	(2.89)	(3.30)	(2.51)		
Additional charge	0.26	0.04	0.12**	0.04	0.100	1005
	[0.44]	(0.04)	(0.05)	(0.04)		
Knowledge gap	0.48	0.02	-0.07	-0.04	0.690	935
	[0.95]	(0.10)	(0.07)	(0.07)		
Irregular local contact share	0.68	-0.08*	-0.08*	-0.07*	0.223	756
	[0.28]	(0.05)	(0.05)	(0.04)		

Notes: In each row, columns (2) through (4) present regression coefficients and standard errors from a regression of the listed variable on treatment arm indicators, with control as the omitted group. Additionally included in each regression are randomization strata fixed effects, as well as an indicator for being a program officer in Panels B and C. Column (1) presents the control group mean and standard deviation. Column (5) presents the p-value from an F-test of the joint hypothesis of zero-valued coefficients on the treatment arm indicators. Column (6) gives the number of observations. Standard errors are heteroskedasticity robust and, in Panels B and C, clustered by district. Variables in Panel A are at the district level and generated from MGNREGS administrative data for the year prior to intervention start (February 2016-January 2017) and 2011 census data. Variables in Panels B and C are at the district and subdistrict officer level, repsectively, and generated from the baseline officer surveys.

Table 2: PayDash usage

	Sessions		Duration (min)		Calls and messages	
	POs	CEOs	POs	CEOs	POs	CEOs
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. District officers						
District Only PayDash	4.39	0.43	26.61	1.48	17.17	0.12
	[9.42]	[1.98]	[71.38]	[8.46]	[68.76]	[1.30]
Combination PayDash	3.18	1.07	13.07	4.14	3.30	0.17
	[6.98]	[3.30]	[35.06]	[18.13]	[13.60]	[1.50]
Difference	-1.91	0.48	-18.98	2.05	-18.49	0.03
	(1.92)	(0.34)	(14.75)	(1.42)	(14.99)	(0.18)
Observations	500	465	500	465	500	465
Panel B. Subdistrict officers						
Subdistrict Only PayDash	3.08	1.29	19.99	5.06	0.52	0.08
	[7.45]	[4.48]	[74.53]	[25.82]	[7.41]	[1.17]
Combination PayDash	4.16	1.58	22.84	5.50	0.85	0.01
	[9.70]	[4.20]	[77.32]	[20.54]	[15.13]	[0.19]
Difference	0.77	0.26	1.89	0.60	0.45	-0.06*
	(0.72)	(0.28)	(5.56)	(1.10)	(0.60)	(0.03)
Observations	3,716	3,633	3,716	3,633	3,716	3,633

Notes: Columns in each panel report means and standard deviations of the listed officer PayDash usage variables, calculated separately by treatment arm at the district-month (Panel A) or subdistrict-month (Panel B) level and restricted to treatment months in localities receiving PayDash at the corresponding officer level. "Sessions" includes both web and mobile usage, while "Duration" captures mobile usage only. Also shown are the coefficients on an indicator for PayDash provision at both officer levels in regressions of the listed variables on that indicator as well as month and strata fixed effects. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 3: PayDash impacts on payment processing and work volume

	Processing time (days)		Above mandate length		Absolute deviation (days)		Log person-days worked	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any PayDash (β)	-1.417***		-0.071**		-0.517**		0.172**	
	(0.382)		(0.034)		(0.226)		(0.069)	
District Only PayDash (β_1)		-1.518**		-0.073		-0.632*		0.287***
		(0.745)		(0.050)		(0.376)		(0.101)
Subdistrict Only PayDash (β_2)		-1.673***		-0.045		-0.498		0.169**
		(0.568)		(0.032)		(0.300)		(0.082)
Combination (β_3)		-1.160**		-0.086		-0.437		0.082
		(0.500)		(0.052)		(0.326)		(0.099)
Observations	14,553	14,553	14,553	14,553	14,553	14,553	14,554	14,554
$\beta_1 + \beta_2 = \beta_3$, p-value		0.041		0.651		0.179		0.006
$\beta_1 = \beta_2 = \beta_3$, p-value		0.742		0.667		0.911		0.230
Control outcome mean	13.25	13.25	0.72	0.72	6.50	6.50	9.31	9.31

Notes: Columns report estimates from regressions at the subdistrict-month level of the listed variable on treatment arm indicators, subdistrict and month fixed effects, and linear controls for district time trends. Control means calculated over pre-intervention period. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 4: Composition of work volume impacts

	Log person-days per working household		Log working households		Log working villages		Log muster rolls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any PayDash (β)	0.086***		0.086		0.057		0.186**	
	(0.019)		(0.070)		(0.044)		(0.079)	
District Only PayDash (β_1)		0.130***		0.157*		0.071		0.234*
		(0.022)		(0.091)		(0.065)		(0.119)
Subdistrict Only PayDash (β_2)		0.116***		0.053		0.076		0.141
		(0.027)		(0.073)		(0.048)		(0.099)
Combination (β_3)		0.030		0.052		0.032		0.178
		(0.029)		(0.104)		(0.067)		(0.113)
Observations	14,554	14,554	14,554	14,554	14,554	14,554	14,553	14,553
$\beta_1 + \beta_2 = \beta_3$, p-value		0.000		0.195		0.195		0.235
$\beta_1 = \beta_2 = \beta_3$, p-value		0.014		0.553		0.803		0.814
Control outcome mean	2.28	2.28	7.03	7.03	4.08	4.08	5.76	5.76

Notes: Columns report estimates from regressions at the subdistrict-month level of the listed variable on treatment arm indicators, subdistrict and month fixed effects, and linear controls for district time trends. Control means calculated over pre-intervention period. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 5: Effects of PayDash on officer work quality and corruption

	Share of payment requests rejected		Audit irregularity index	
	(1)	(2)	(3)	(4)
Any PayDash (β)	-0.007		-0.029	
	(0.005)		(0.056)	
District Only PayDash (β_1)		-0.006		0.004
		(0.007)		(0.070)
Subdistrict Only PayDash (β_2)		0.003		-0.030
		(0.008)		(0.056)
Combination (β_3)		-0.015**		-0.063
		(0.006)		(0.056)
Observations	14,266	14,266	20,621	20,621
$\beta_1 + \beta_2 = \beta_3$, p-value		0.338		0.621
$\beta_1 = \beta_2 = \beta_3$, p-value		0.188		0.289
Control outcome mean	0.052	0.052	0.000	0.000

Notes: Columns (1) and (2) report estimates from regressions at the subdistrict-month level of the listed variable on treatment arm indicators, subdistrict and month fixed effects, and linear controls for district time trends. Columns (3) and (4) report estimates from regressions at the audit level of the listed variable on treatment indicators and strata fixed effects. Control means calculated over pre-intervention period in columns (1) and (2). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 6: PayDash impacts on posting transfers, program demand, and officer knowledge

	Subdistrict posting transfer		Community work demand		Officer knowledge gap	
	(1)	(2)	(3)	(4)	(5)	(6)
Any PayDash (β)	-0.057		0.124**		-0.078*	
	(0.044)		(0.061)		(0.042)	
District Only PayDash (β_1)		-0.106**		0.088		-0.067
		(0.051)		(0.076)		(0.056)
Subdistrict Only PayDash (β_2)		0.029		0.102		-0.100**
		(0.055)		(0.076)		(0.048)
Combination (β_3)		-0.073		0.183**		-0.072
		(0.051)		(0.074)		(0.048)
Observations	1,122	1,122	20,621	20,621	176	176
$\beta_1 + \beta_2 = \beta_3$, p-value		0.955		0.944		0.192
$\beta_1 = \beta_2 = \beta_3$, p-value		0.036		0.435		0.780
Control outcome mean	0.447	0.447	0.297	0.297	0.418	0.418

Notes: Columns (1) and (2) report estimates from regressions at the subdistrict-position level of the listed variable on treatment arm indicators as well as strata and position fixed effects. Columns (3) and (4) report estimates from regressions at the audit level of the listed variable on treatment indicators and strata fixed effects. Columns (5) and (6) report estimates from regressions at the subdistrict PO level of the listed variable on treatment arm indicators as well as strata fixed effects. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 7: Heterogeneity in PayDash impacts by administrative structure

	Processing time (days)		Above mandate length		Absolute deviation (days)		Log person-days worked	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High GPs per subdistrict								
*Any PayDash (θ)	-2.559***		-0.142***		-1.118***		0.047	
	(0.740)		(0.051)		(0.388)		(0.109)	
*District Only PayDash (θ_1)		-3.331**		-0.205***		-1.605**		0.183
		(1.502)		(0.074)		(0.743)		(0.218)
*Subdistrict Only PayDash (θ_2)		-2.388***		-0.063		-0.910**		0.063
		(0.872)		(0.050)		(0.454)		(0.124)
*Combination (θ_3)		-1.970**		-0.169**		-0.880*		-0.087
		(0.972)		(0.080)		(0.511)		(0.107)
Low GPs per subdistrict								
*Any PayDash (λ)	-0.677*		-0.024		-0.127		0.254***	
	(0.399)		(0.039)		(0.238)		(0.072)	
*District Only PayDash (λ_1)		-0.482		0.003		-0.079		0.332***
		(0.585)		(0.050)		(0.292)		(0.082)
*Subdistrict Only PayDash (λ_2)		-0.945		-0.036		-0.074		0.282***
		(0.853)		(0.043)		(0.365)		(0.092)
*Combination (λ_3)		-0.713		-0.041		-0.192		0.175
		(0.518)		(0.067)		(0.399)		(0.124)
Observations	14,553	14,553	14,553	14,553	14,553	14,553	14,554	14,554
$\theta = \lambda$, p-value	0.027		0.038		0.021		0.069	
$\theta_1 + \theta_2 = \theta_3$, p-value		0.053		0.363		0.091		0.193
$\lambda_1 + \lambda_2 = \lambda_3$, p-value		0.505		0.928		0.945		0.006
$\theta_1 = \theta_2 = \theta_3$, p-value		0.724		0.092		0.652		0.319
$\lambda_1 = \lambda_2 = \lambda_3$, p-value		0.895		0.802		0.963		0.504
Control outcome mean (high)	16.79	16.79	0.91	0.91	7.17	7.17	9.29	9.29
Control outcome mean (low)	12.22	12.22	0.66	0.66	6.31	6.31	9.31	9.31

Notes: Columns report estimates from regressions at the subdistrict-month level of the listed variable on treatment indicators interacted with above- and below-median average number of GPs per subdistrict indicators. Also included are subdistrict fixed effects, month fixed effects, and linear controls for district time trends. Control means calculated over pre-intervention period. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 8: Association of administrative structure and workload

	Workload index			
	Subdistrict officers		District officers	
	(1)	(2)	(3)	(4)
High GPs per subdistrict	0.168**		0.174	
	(0.073)		(0.168)	
High subdistricts per district	-0.031		0.029	
	(0.057)		(0.143)	
GPs per subdistrict		0.005**		-0.005
		(0.002)		(0.005)
Subdistricts per district		0.000		0.007
		(0.006)		(0.019)
Observations	523	523	71	71
Outcome mean	-0.001	-0.001	-0.021	-0.021

Notes: Columns (1) and (3) report estimates from regressions at the baseline program officer level of the listed variable on an indicator for being an above-median district in terms of average number of panchayats per subdistrict and an indicator for being an above-median district in terms of number of subdistricts. Columns (2) and (4) report estimates from regressions at the baseline program officer level of the listed variable on the district-level average number of panchayats per subdistrict and the number of subdistricts. Also included is a state indicator. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Appendix A: Figures and Tables

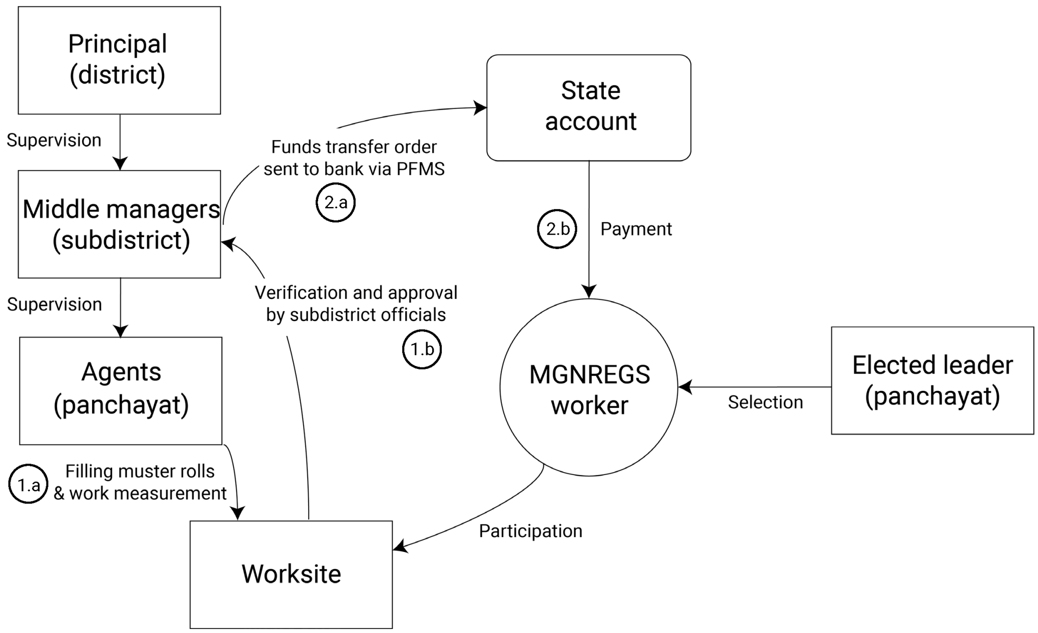
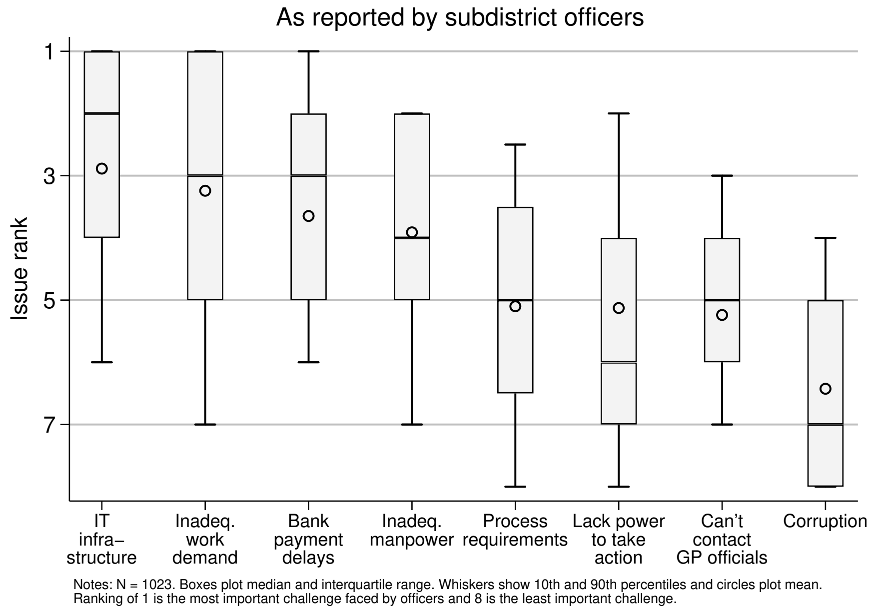


Figure A1: MGNREGS work, verification, and payment process

(a) Administrator challenges



(b) Worker challenges

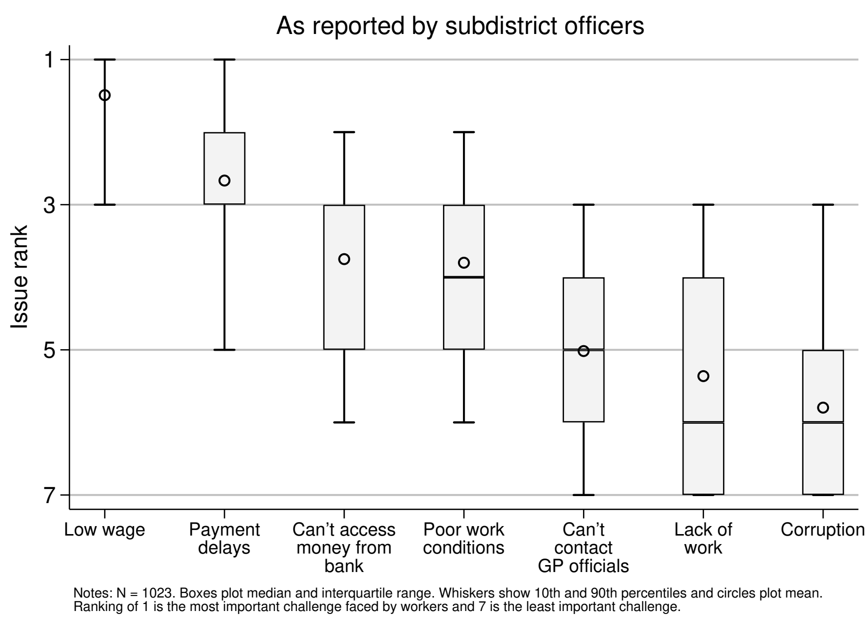


Figure A2: Challenges faced by MGNREGS administrators and workers

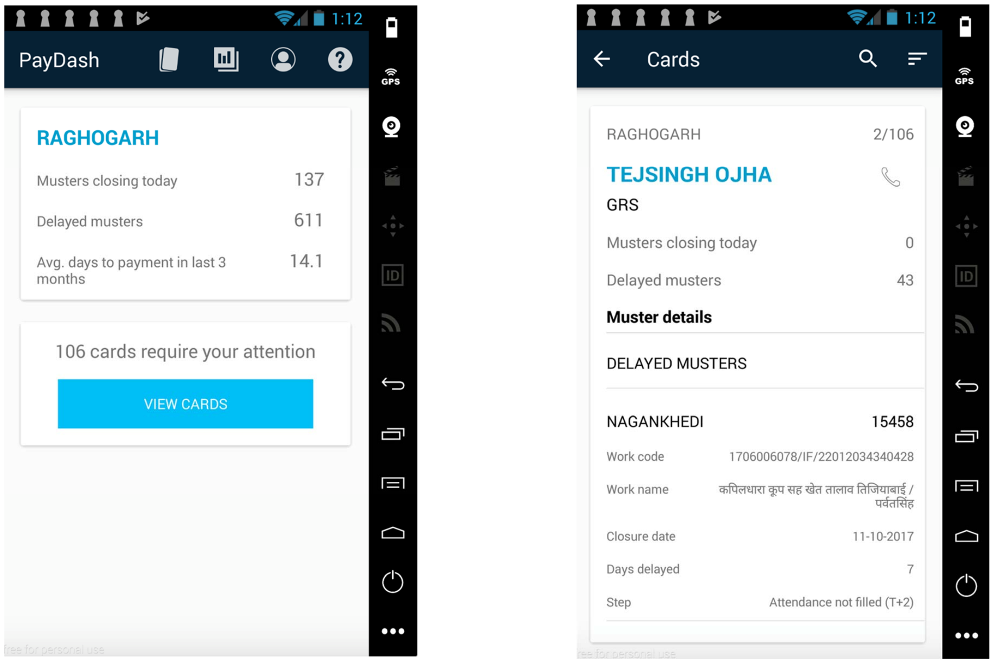


Figure A3: PayDash app home screen providing a daily-updated overview of payment processing status within an officer's jurisdiction (L). App screen with information about a local official. The app shows payment documents pending and allows officers to directly contact the individual responsible for processing the document. (R)

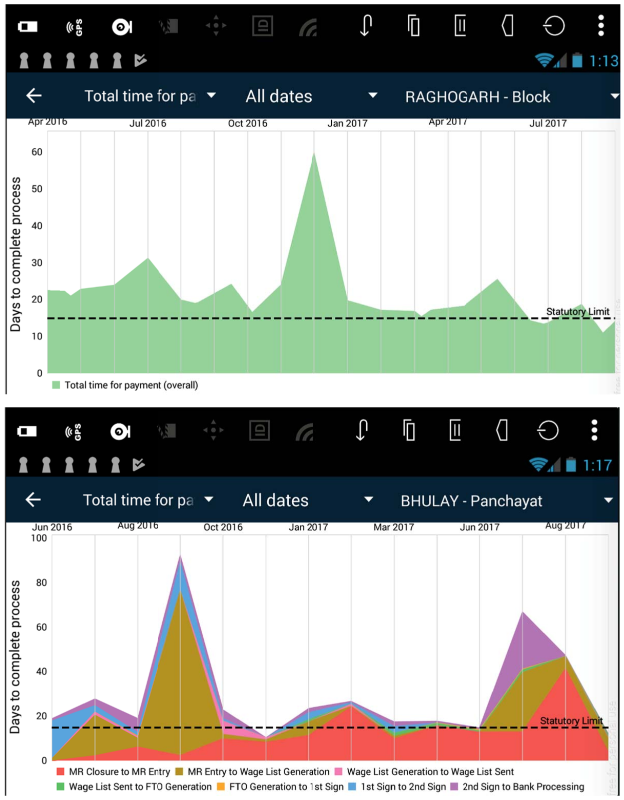


Figure A4: The performance dashboard of the Block PayDash app provides a historical overview of subdistrict and village-level performance.

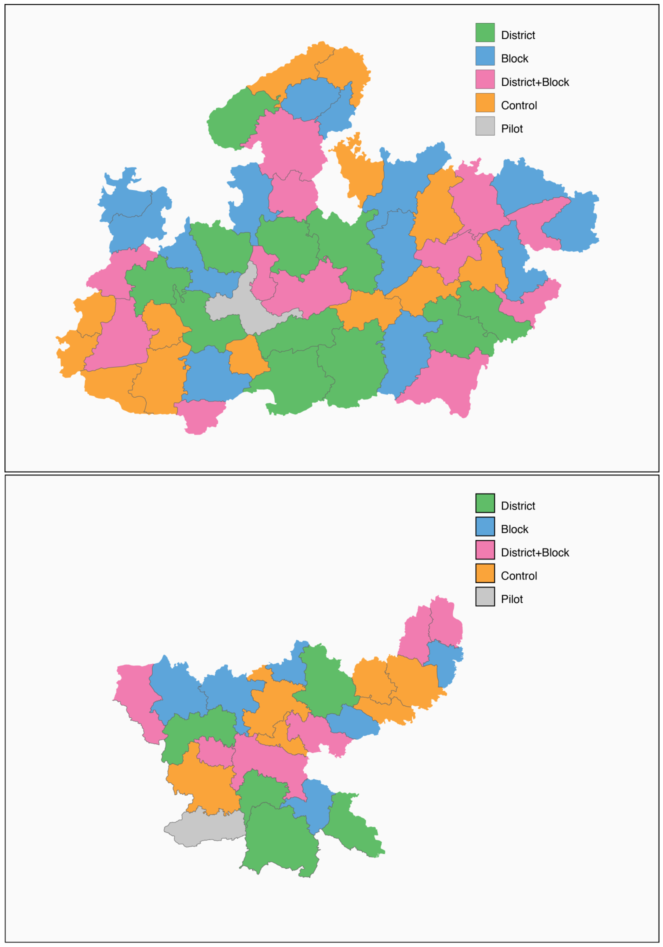


Figure A5: District randomized treatment assignments - Madhya Pradesh (top) and Jharkhand (bottom)

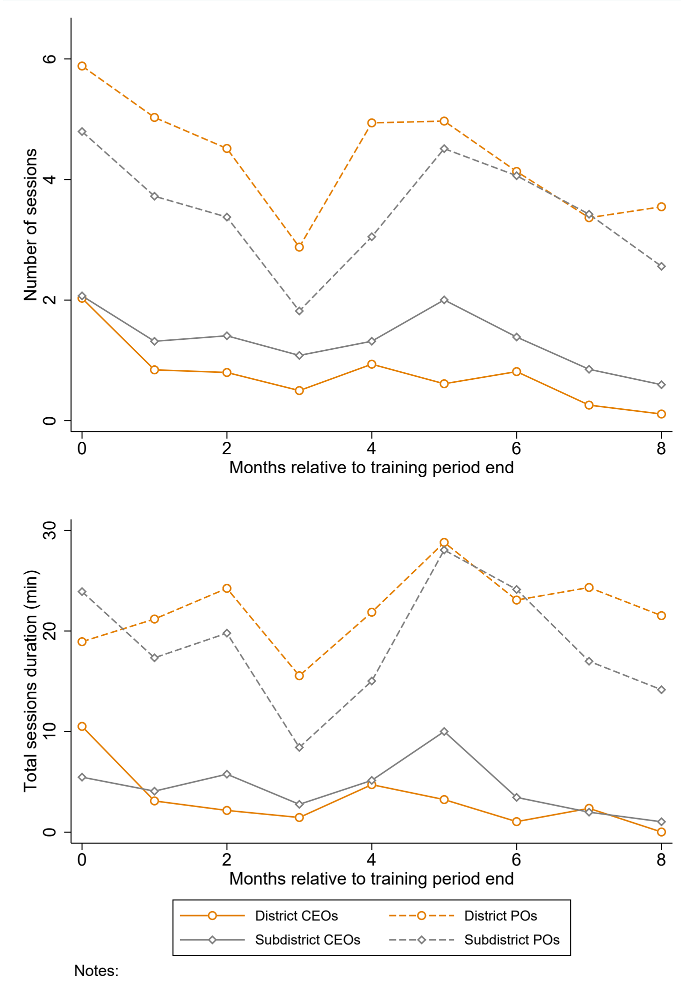


Figure A6: PayDash usage over time

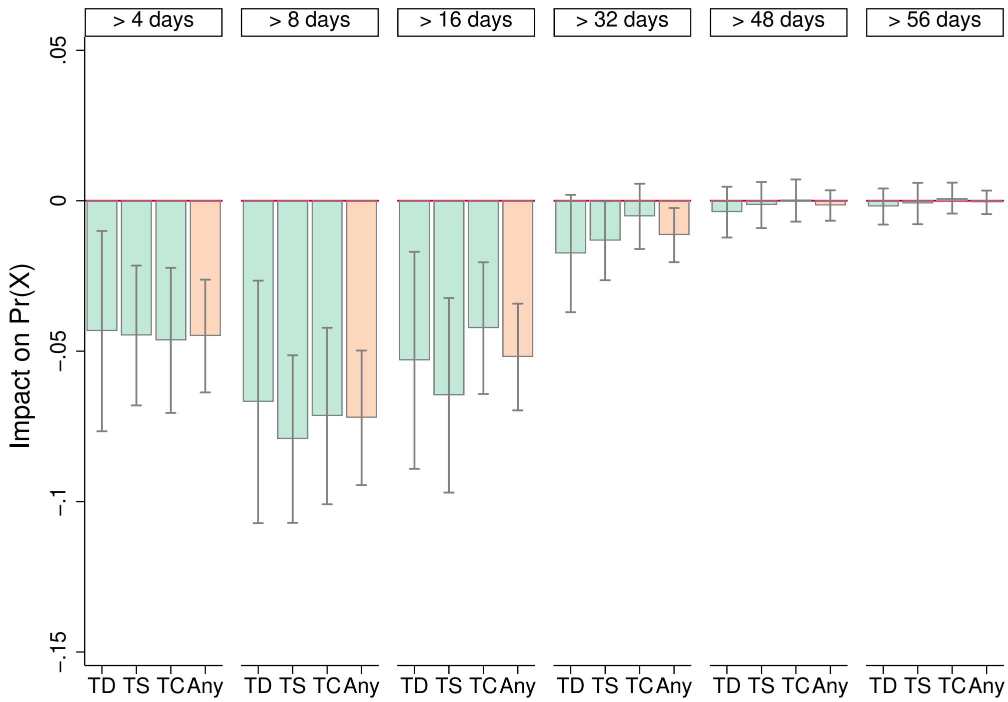


Figure A7: Impacts of PayDash on exceeding processing time thresholds - by treatment arm

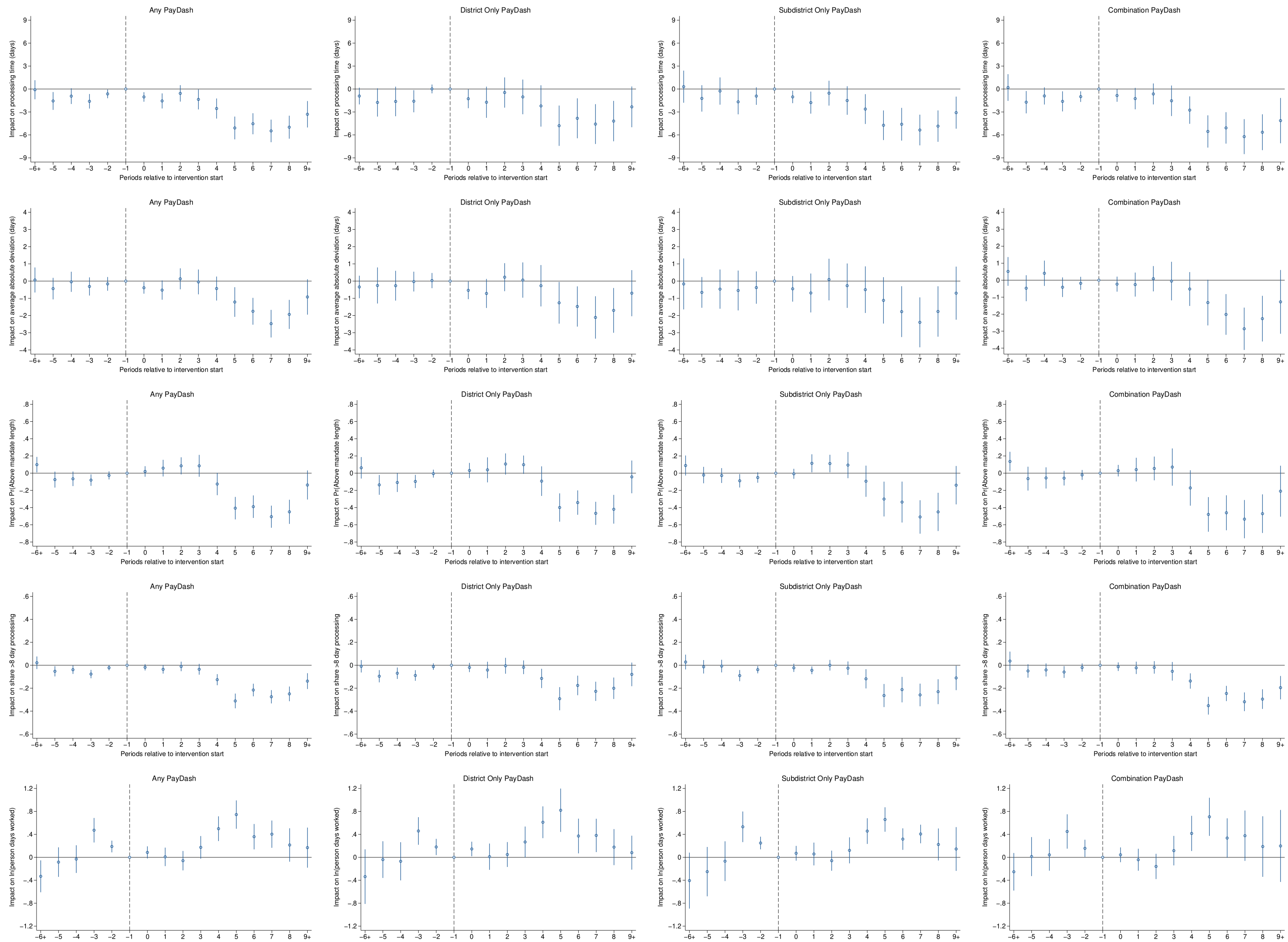


Figure A8: PayDash impacts - by treatment arm

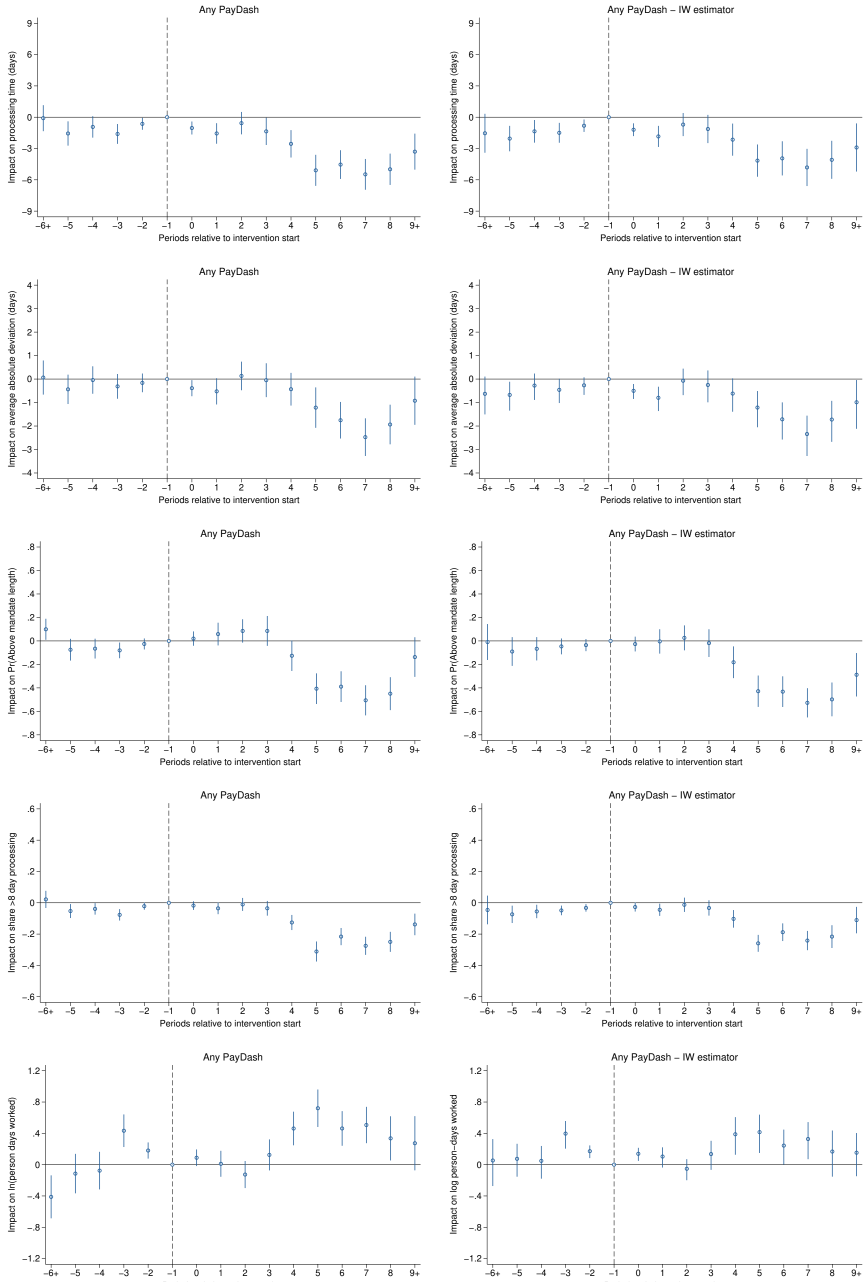


Figure A9: IW estimator comparison

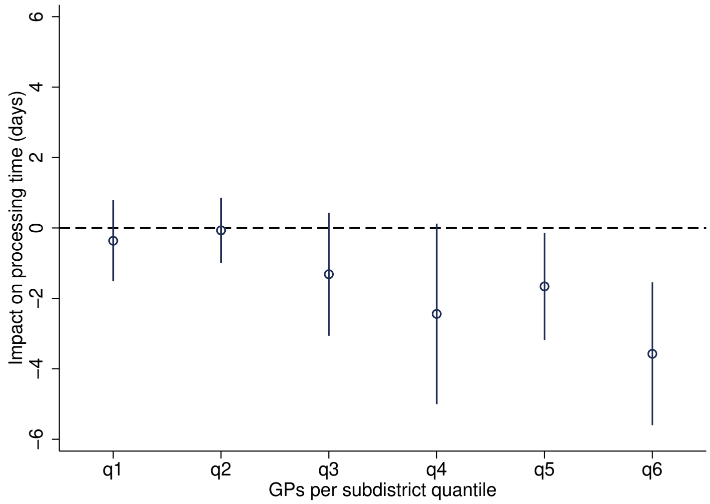


Figure A10: Heterogeneity in PayDash impact by administrative structure

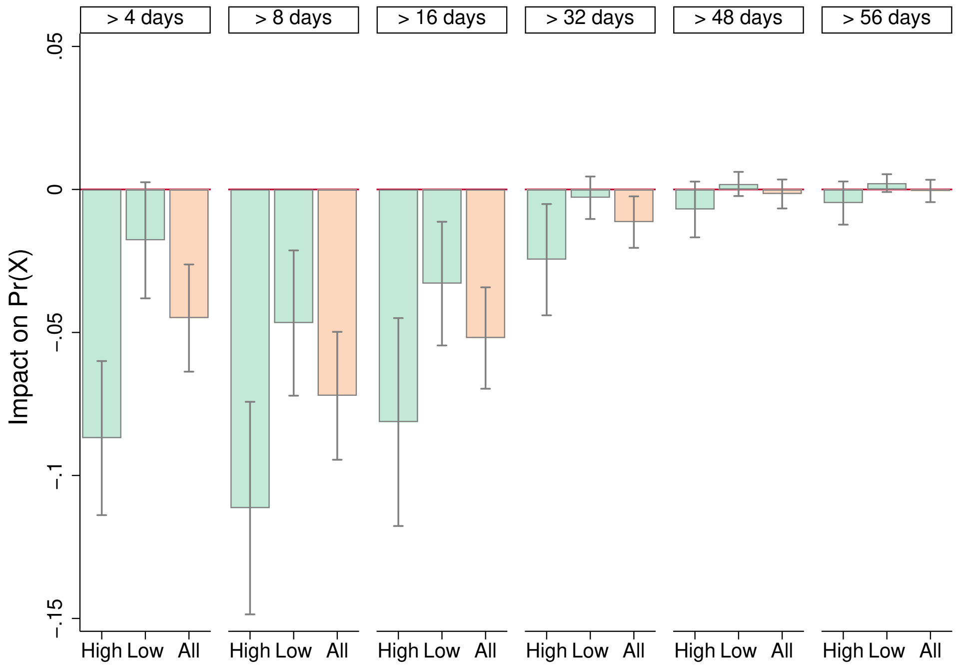


Figure A11: PayDash impacts on exceeding processing time thresholds - by GPs per subdistrict

Table A1: Additional baseline characteristics

	Control Mean (1)	District Only (2)	Subdistrict Only (3)	Combination (4)	Joint p-value (5)	Obs (6)
Person-days per working household	13.52	0.83	-0.96	-0.00	0.670	73
	[3.25]	(1.37)	(1.08)	(1.09)		
Working households (x1,000)	11.15	3.55	0.31	2.32	0.377	73
	[6.69]	(2.44)	(1.63)	(2.41)		
Working villages	450.30	77.67	40.68	22.20	0.812	73
	[236.13]	(82.84)	(64.55)	(80.40)		

Notes: In each row, columns (2) through (4) present regression coefficients and standard errors from a regression of the listed variable on treatment arm indicators, with control as the omitted group. Additionally included in each regression are strata fixed effects. Column (1) presents the control group mean and standard deviation. Column (5) presents the p-value from an F-test of the joint significance of the three treatment arm indicators. Column (6) gives the number of observations. Standard errors are heteroskedasticity robust. Variables are district-level monthly averages over the year prior to intervention start (February 2016-January 2017), generated from MGNREGS administrative data.

Table A2: MGNREGS worker composition

	Below poverty line		Female	
	(1)	(2)	(3)	(4)
Any PayDash (β)	0.003**		-0.002	
	(0.001)		(0.002)	
District Only PayDash (β_1)		0.004**		0.001
		(0.002)		(0.004)
Subdistrict Only PayDash (β_2)		0.000		-0.004
		(0.003)		(0.004)
Combination (β_3)		0.004*		-0.003
		(0.002)		(0.004)
Observations	14,554	14,554	14,554	14,554
$\beta_1 + \beta_2 = \beta_3$, p-value		0.939		0.969
$\beta_1 = \beta_2 = \beta_3$, p-value		0.421		0.499
Control outcome mean	0.182	0.182	0.382	0.382

Notes: Columns report estimates from regressions at the subdistrict-month level of the listed variable on treatment arm indicators, subdistrict and month fixed effects, and linear controls for district time trends. Control means calculated over pre-intervention period. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A3: Impacts on officer transfers - longer term

	Subdistrict posting transfer (6 months)		Subdistrict posting transfer (17 months)	
	(1)	(2)	(3)	(4)
Any PayDash (β)	-0.045		-0.079	
	(0.062)		(0.050)	
District Only PayDash (β_1)		-0.118*		-0.123*
		(0.069)		(0.063)
Subdistrict Only PayDash (β_2)		0.054		-0.012
		(0.069)		(0.058)
Combination (β_3)		-0.049		-0.088
		(0.074)		(0.061)
Observations	616	616	616	616
$\beta_1 + \beta_2 = \beta_3$, p-value		0.873		0.593
$\beta_1 = \beta_2 = \beta_3$, p-value		0.026		0.167
Control outcome mean	0.660	0.660	0.773	0.773

Notes: Columns report estimates from regressions at the subdistrict-position level of the listed variable on treatment indicators as well as strata and position fixed effects. The sample is restricted to Madhya Pradesh, as the 17-month measure is only available in that state. Standard errors clustered at the district level in parentheses. Significant at *10 percent,**5 percent,***1 percent.

Table A4: Synthetic DID comparison

	Processing time (days)	Above mandate length	Pr (>8 day processing)	Absolute deviation (days)	Log muster rolls	Log person-days worked	Log person-days per working household	Log working households	Log working villages	Share of payment requests rejected
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Any PayDash, Primary	-1.369***	-0.071**	-0.071***	-0.531**	0.182**	0.167**	0.084***	0.083	0.053	-0.007
	(0.379)	(0.034)	(0.013)	(0.227)	(0.080)	(0.071)	(0.019)	(0.071)	(0.046)	(0.005)
Any PayDash, Synthetic Diff-in-Diff	-1.126***	-0.031	-0.055***	0.125	0.146**	0.129**	0.094***	0.062	0.036**	0.001
	(0.388)	(0.020)	(0.013)	(0.201)	(0.059)	(0.054)	(0.015)	(0.043)	(0.015)	(0.003)
Observations	14,586	14,586	14,586	14,586	14,586	14,586	14,586	14,586	14,586	14,586
Control outcome mean	13.252	0.719	0.541	6.505	5.757	9.307	2.281	7.027	4.083	0.053

Notes: Each column reports estimates from two regressions at the subdistrict-month level for the listed variable. Primary indicates estimation using the specification given in equation (1) of the main text. Synthetic Diff-in-Diff indicates estimation using the corresponding synthetic difference-in-differences approach (Arkhangelsky et al. 2021) with 200 bootstrap replications. Control means calculated over pre-intervention period.To generate the balanced panel necessary for the SDID approach, missing values for interior panel months linearly interpolated and panel periods that cannot be interpolated replaced with the district-month average. Significant at *10 percent, **5 percent,***1 percent.

Table A5: Audit index - components

	Any financial deviation		Any financial misappropriation		Any grievance		Any process violation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any PayDash (β)	-0.012		-0.006		-0.010		-0.010	
	(0.026)		(0.016)		(0.019)		(0.035)	
District Only PayDash (β_1)		0.002		0.004		-0.007		0.007
		(0.028)		(0.018)		(0.027)		(0.043)
Subdistrict Only PayDash (β_2)		-0.012		-0.010		-0.002		-0.018
		(0.026)		(0.016)		(0.022)		(0.035)
Combination (β_3)		-0.028		-0.011		-0.022		-0.019
		(0.026)		(0.017)		(0.019)		(0.037)
Observations	20,621	20,621	20,621	20,621	20,621	20,621	20,621	20,621
$\beta_1 + \beta_2 = \beta_3$, p-value		0.528		0.803		0.668		0.858
$\beta_1 = \beta_2 = \beta_3$, p-value		0.059		0.320		0.487		0.669
Control outcome mean	0.122	0.122	0.102	0.102	0.135	0.135	0.192	0.192

Notes: Columns report estimates from regressions at the audit level of the listed variable on treatment indicators and strata fixed effects, restricted to post-intervention observations. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A6: Impact heterogeneity - composition of work volume impacts

	Log person-days per working household		Log working households		Log working villages		Log muster rolls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High GPs per subdistrict								
*Any PayDash (θ)	0.097***		-0.050		0.082		0.108	
	(0.029)		(0.103)		(0.067)		(0.133)	
*District Only PayDash (θ_1)		0.138***		0.045		0.120		0.156
		(0.043)		(0.191)		(0.132)		(0.233)
*Subdistrict Only PayDash (θ_2)		0.096***		-0.032		0.101		0.090
		(0.033)		(0.120)		(0.076)		(0.176)
*Combination (θ_3)		0.068*		-0.155		0.024		0.091
		(0.035)		(0.104)		(0.082)		(0.175)
Low GPs per subdistrict								
*Any PayDash (λ)	0.079***		0.175**		0.041		0.236***	
	(0.029)		(0.069)		(0.047)		(0.081)	
*District Only PayDash (λ_1)		0.126***		0.206***		0.041		0.272**
		(0.022)		(0.077)		(0.056)		(0.120)
*Subdistrict Only PayDash (λ_2)		0.145***		0.137**		0.047		0.194***
		(0.050)		(0.064)		(0.051)		(0.057)
*Combination (λ_3)		0.009		0.166		0.037		0.226*
		(0.043)		(0.125)		(0.084)		(0.133)
Observations	14,554	14,554	14,554	14,554	14,554	14,554	14,553	14,553
$\theta = \lambda$, p-value	0.697		0.023		0.553		0.355	
$\theta_1 + \theta_2 = \theta_3$, p-value		0.004		0.462		0.224		0.627
$\lambda_1 + \lambda_2 = \lambda_3$, p-value		0.000		0.215		0.624		0.154
$\theta_1 = \theta_2 = \theta_3$, p-value		0.314		0.430		0.653		0.963
$\lambda_1 = \lambda_2 = \lambda_3$, p-value		0.028		0.781		0.993		0.826
Control outcome mean (high)	2.56	2.56	6.73	6.73	4.08	4.08	5.48	5.48
Control outcome mean (low)	2.20	2.20	7.11	7.11	4.08	4.08	5.84	5.84

Notes: Columns report estimates from regressions at the subdistrict-month level of the listed variable on treatment indicators interacted with above- and below-median average number of GPs per subdistrict indicators. Also included are subdistrict fixed effects, month fixed effects, and linear controls for district time trends. Control means calculated over pre-intervention period. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A7: Impact heterogeneity - quality, transfers, knowledge, and program demand

	Share of payment requests rejected		Audit irregularity index		Subdistrict posting transfer		Subdistrict knowledge gap		Community work demand	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High GPs per subdistrict										
*Any PayDash (θ)	0.000		-0.066		-0.015		-0.057		0.116*	
	(0.008)		(0.052)		(0.055)		(0.044)		(0.069)	
*District Only PayDash (θ_1)		0.007		-0.065		-0.069		-0.039		0.051
		(0.012)		(0.056)		(0.067)		(0.056)		(0.087)
*Subdistrict Only PayDash (θ_2)		0.009		-0.060		0.031		-0.088		0.109
		(0.012)		(0.055)		(0.064)		(0.054)		(0.090)
*Combination (θ_3)		-0.017*		-0.066		-0.030		-0.042		0.182**
		(0.010)		(0.051)		(0.080)		(0.055)		(0.083)
Low GPs per subdistrict										
*Any PayDash (λ)	-0.013**		0.041		-0.079		-0.128**		0.139*	
	(0.006)		(0.074)		(0.049)		(0.053)		(0.080)	
*District Only PayDash (λ_1)		-0.014*		0.099		-0.123**		-0.112		0.145
		(0.008)		(0.102)		(0.057)		(0.090)		(0.111)
*Subdistrict Only PayDash (λ_2)		-0.005		0.060		0.032		-0.164***		0.072
		(0.009)		(0.070)		(0.077)		(0.052)		(0.060)
*Combination (λ_3)		-0.014*		-0.066		-0.095*		-0.140**		0.180
		(0.008)		(0.078)		(0.054)		(0.058)		(0.127)
Observations	14,266	14,266	20,621	20,621	1,122	1,122	176	176	20,621	20,621
$\theta = \lambda$, p-value	0.164		0.040		0.267		0.169		0.786	
$\theta_1 + \theta_2 = \theta_3$, p-value		0.089		0.380		0.938		0.268		0.869
$\lambda_1 + \lambda_2 = \lambda_3$, p-value		0.724		0.074		0.968		0.275		0.823
$\theta_1 = \theta_2 = \theta_3$, p-value		0.141		0.972		0.362		0.666		0.374
$\lambda_1 = \lambda_2 = \lambda_3$, p-value		0.690		0.154		0.154		0.806		0.444
Control outcome mean (high)	0.062	0.062	-0.221	-0.221	0.679	0.679	0.422	0.422	0.219	0.219
Control outcome mean (low)	0.050	0.050	0.409	0.409	0.320	0.320	0.422	0.422	0.440	0.440

Notes: All columns report estimates from regression of the listed variable on treatment indicators interacted with above- and below-median average number of GPs per subdistrict indicators. Columns (1) and (2) report estimates from subdistrict-month-level regressions which also include subdistrict and month fixed effects, as well as linear controls for district time trends. Columns (3), (4), (9), and (10) report estimates from audit-level regressions which also include strata fixed effects. Columns (5) and (6) report estimates from subdistrict-position-level regressions which also include strata and position fixed effects. Columns (7) and (8) report estimates from subdistrict-PO-level regressions which also include strata fixed effects. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A8: PayDash usage heterogeneity

	District officers		Subdistrict officers	
	Sessions	Duration (min)	Sessions	Duration (min)
	(1)	(2)	(3)	(4)
High GPs per subdistrict	3.65***	17.06*	-0.36	-4.82
	(1.27)	(8.72)	(0.86)	(8.77)
Observations	500	500	3,716	3,716
Outcome mean	3.73	19.19	4.55	25.01

Notes: Columns report estimates from regressions at the district- or subdistrict-month level of the listed program officer PayDash usage variable on an indicator for being an above-median district in terms of average number of panchayats per subdistrict, month and strata fixed effects, and an indicator for PayDash provision at both officer levels. The sample is restricted to treatment months in localities receiving PayDash at the corresponding officer level. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A9: Workload index - components

	Hours worked per week		Calls per work day		Additional charge		Knowledge gap		Irregular local contact share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Subdistrict POs										
GPs per subdistrict	-0.126		0.386***		0.004		-0.003		0.005***	
	(0.088)		(0.127)		(0.002)		(0.004)		(0.001)	
Subdistricts per district	-0.080		0.188		0.001		-0.012		0.003	
	(0.317)		(0.299)		(0.008)		(0.016)		(0.005)	
High GPs per subdistrict		-0.314		6.544*		0.184**		0.079		0.036*
		(3.022)		(3.408)		(0.073)		(0.076)		(0.020)
High subdistricts per district		-2.062		-2.379		0.070		0.013		-0.053
		(2.730)		(3.138)		(0.054)		(0.073)		(0.034)
Observations	506	506	506	506	512	512	482	482	444	444
Outcome mean	75.415	75.415	45.856	45.856	0.250	0.250	0.491	0.491	0.617	0.617
Panel B: District POs										
GPs per subdistrict	0.016		0.256		-0.014***		-0.001			
	(0.211)		(0.274)		(0.004)		(0.002)			
Subdistricts per district	-0.045		1.423		-0.034**		0.017			
	(0.626)		(0.927)		(0.016)		(0.013)			
High GPs per subdistrict		6.682		10.620*		-0.132		0.070		
		(5.994)		(5.921)		(0.152)		(0.090)		
High subdistricts per district		-0.182		6.138		-0.044		-0.007		
		(4.497)		(6.384)		(0.121)		(0.102)		
Observations	68	68	68	68	71	71	66	66		
Outcome mean	70.162	70.162	39.963	39.963	0.493	0.493	0.368	0.368		

Notes: The first column for each of the outcome variables report estimates from regressions at the baseline officer level of the listed variable on the average number of panchayats per subdistrict and the number of subdistricts. The second column for each of the outcome variables report estimates from regressions at the baseline officer level of the listed variable on an indicator for being an above-median district in terms of average number of panchayats per subdistrict and an indicator for being an above-median district in terms of number of subdistricts. Also included is a state fixed effect. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Appendix B

B.1 PayDash training

To introduce officers to PayDash, we invited all relevant government officials in the study area - typically a permanent district officer overseeing multiple development schemes in their district, the contract district worker specifically overseeing MGNREGS, a permanent block officer overseeing multiple development schemes in the block, and a contract block officer specifically overseeing only MGNREGS in the block - to a half-day session.

Both control and treatment officials went through the same roll-out process, with the exception that only treatment officials were introduced to and provided PayDash. First, we collected baseline survey data from all officials through a self-administered, paper survey. Then we conducted a session outlining data-based management tools available to officials in the MGNREGS MIS and asked officials to share about their work and professional challenges they face.

After this, control officials were dismissed. In sessions with treatment officers, the training continued with an additional 1.5 hour session where officers were introduced to PayDash and its mobile platform, and they downloaded the app and conducted preliminary exercises on the platform to ensure it was functional and they understood how to use it. To avoid treatment contamination, officers from treatment areas were trained on separate days and/or locations from those in control areas. To encourage survey response and PayDash coverage, we made extensive efforts (by calling up to five times on different dates, and having the state send a letter instructing all officials to report for this official training) to maximize the likelihood of officer presence at the training sessions during the state roll-out.

For those officials that did not attend the group-based training, we conducted individual surveying and onboarding to PayDash (when relevant). To avoid sensitivities related to officials' seniority, we conducted sessions separately not only for treatment and control officials, but also for block and district-level officials within these groups.

B.2 Randomization strata

The district-level average processing time measure used in defining the randomization strata was calculated across muster-roll-by-workers reaching processing completion within each district over the April 2015 to May 2016 range for Madhya Pradesh and the April 2015 to June 2016 range for Jharkhand. The district-level per-block volume of person-days worked measure used was the average of the block-level monthly totals of person-days worked across blocks within each district, over the April 2015 to April 2016 range for Madhya Pradesh and the April 2015 to June 2016 range for Jharkhand. These measures were constructed using the more limited administrative data available to us at the time of randomization.

B.3 Social audits

As described in the main text, social audits are community (GP)-level exercises intended to assess the quality of local service delivery and improve implementation and accountability of implementation of MGNREGS and other local social assistance programs.

The central government has outlined audit guidelines, while states decide where and when to conduct audits. In Jharkhand, GPs were randomly assigned to be audited on an annual basis. The timing of audits within the assigned fiscal year tended to concentrate audits within the same district at one time to ensure audits were completed prior to scheduled hearings that were intended to resolve larger issues. Exact audit timing was also based on logistical feasibility. In Madhya Pradesh, the state selected subdistricts that would be audited for a given fiscal year prior to that year. Targeted subdistricts were rotated to maximize audit location coverage across years. Within a given quarter, all GPs in one selected subdistrict in each district were targeted to be audited. We do not observe that GP audit probability differs significantly by district treatment status.

Audits typically last just over one week and include visits by independent auditors from outside the community to households listed as having worked for MGNREGS to verify accuracy of records, visits to MGNREGS worksites to assess assets created compared to written records, and reviews of documentation maintained related to work quality and completeness.

After a week of fact-finding and verification has been completed by the audit team, communities hold local meetings known as “Gram Sabhas”, where audit findings are discussed in a public forum and workers can discuss disputes with local leaders. Following this meeting, auditors that visited the locality upload a report from the audit. Reports include issues raised and officially filed in the Gram Sabha, as well as an audit checklist that records observations the auditors made during visits with rural households listed in MGNREGS administrative data and to worksites, and through their review of relevant documentation. Departments can then choose to take action against offenders named in the audit reports, and issues filed are only resolved when action has been taken to address and compensate for the problem raised.

In our analysis, we examine the officially-filed audit issues for audits whose assigned reference period, which typically covers 11 months, overlapped at all in the post-intervention analysis period (10 months for Jharkhand and 17 months for Madhya Pradesh).