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# FROM DELAY TO PAYDAY:
# EASING BUREAUCRAT ACCESS TO IMPLEMENTATION INFORMATION STRENGTHENS SOCIAL PROTECTION DELIVERY

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**ABSTRACT**

Poor implementation frequently impedes social protection delivery in low-state-capacity settings. In such environments, reducing managers' information acquisition costs may improve their grasp of frontline issues and program performance. However, in the presence of managerial rent-seeking, increasing the principal's information may be key, and doing so just for managers can backfire. To assess this trade-off and implications for program performance, we collaborated with two Indian states to randomly vary bureaucrat access to “PayDash”, a digital platform for real-time tracking of worker payment processing for the national rural workfare program. In treated districts, PayDash expedited bureaucrat processing of workfare payments by 17%, and increased available worksites and participating household work days by 23% and 10%, respectively. Work provision rose relatively more during the agricultural lean season. PayDash has the same impact when offered to principals as to managers, and no further gains when offered to both, indicating that manager effort to acquire information constrains implementation. Consistent with information allowing principals to better condition performance incentives on managerial effort, PayDash for principals reduced manager posting transfers by 24%. PayDash strengthened state capacity at a considerably lower cost than hiring staff, while benefiting rural Indians by more than 170 times the costs.

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# 1 Introduction

> *. . . when the rights of tens of thousands of people are affected by delayed payment of their legitimate dues, there is a clear constitutional breach committed by the State - be it the Government of India or a State Government.* Supreme Court of India (2016)

One-quarter of the global population receives government payments (World Bank 2022). However, timely delivery of these payments is typically worse where it matters the most: in lower-income countries where state capacity is weak and the majority of the world's extreme poor reside (Page and Pande 2018). Payment delays can force the world's poorest to choose between hunger and expensive loans, exacerbating their poverty. Digital payment systems are often considered a panacea, but continued requirements for human administrative approvals may cause bureaucratic delays to persist (Chopra et al. 2024).[1] That said, using data generated by activity in such digital systems to improve information flows within the bureaucracy could improve management and reduce costly payment delays. In practice, whether this occurs depends on the underlying constraint: Was gathering information too costly for overburdened bureaucrats, or were managers using information to reap rents rather than improve program performance?

Consider a stylized representation of the bureaucratic structure tasked with implementing social protection programs, featuring a principal, a manager, and frontline personnel. If the manager lacks knowledge of frontline implementation challenges, lowering his cost of acquiring information can improve program performance (Aghion and Tirole 1997; Mookherjee 2006). However, if managerial rent-seeking is the relevant constraint, enhancing the principal's information is critical, as doing so solely for managers will backfire (Dixit 2002; Khan et al. 2019). Separately, if the principal designs managerial incentive contracts to minimize her effort costs, then lowering her information acquisition cost has the added benefit of increasing the likelihood of incentives, such as reassigning bureaucrats, being conditioned on manager effort rather than on realized program outcomes (Iyer and Mani 2012; Carroll and Bolte 2023).

[1] Gentilini et al. (2022) document over 1,800 social protection programs in 214 countries in 2020, with digital government-to-person transfers accounting for a growing share of payments. For example, 63% of COVID-related transfers in lower-income countries occurred through digital infrastructure.

We conducted a large-scale experiment with bureaucrats who administer India's workfare program, the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS), in the states of Madhya Pradesh and Jharkhand to evaluate this trade-off and determine how reducing bureaucrats' information acquisition costs impacts MGNREGS implementation. Under MGNREGS, which was implemented following India's 2005 Right to Work Act, rural households can annually demand up to 100 days of manual work, with wage payment supposed to occur within 15 days. During our intervention year of 2017-18, over 50 million Indian households earned more than USD 6 billion from MGNREGS. The majority of this work occurs in the agricultural lean season, typically the four pre-monsoon months in late spring and summer. Multiple studies show positive program impacts on participating households' well-being (Imbert and Papp 2015; Deininger and Liu 2019; Klonner and Oldiges 2022; Muralidharan et al. 2023), particularly during the agricultural lean season. However, payment delays can undermine MGNREGS' premise of helping households smooth income and consumption (Muralidharan et al. 2016; Basu et al. 2024). This, in turn, lowers the value of program participation and increases reliance on alternative coping strategies that risk exploitation (Narayanan et al. 2017; Dréze 2020).[2]

Our intervention included over 1,200 bureaucrats located across 73 districts and 561 subdistricts, and ran from February 2017–August 2018. These bureaucrats were responsible for delivering MGNREGS for the entirety of Jharkhand and Madhya Pradesh, which have a combined population of over 100 million, more than a quarter of whom are rural poor.[3] Districts were randomly assigned to control or one of three treatment groups, in which subdistrict officers (managers), district supervisors (principals), or both received "PayDash", a mobile- and web-based application that tracks pending worker payments using timestamps from the government's online work verification and payment processing system. Relative to the status quo government website, the platform reduces the effort required to obtain program implementation information. Treated officials were encouraged, but not compelled,

[2]Recognizing this, the Supreme Court 2016 judgment also notes: "...delay in payment of wages acts as a disincentive to those persons who are intending to take the benefit of the Scheme."

[3]Districts are the largest within-state administrative unit. Within a district, district officers constitute program principals who oversee subdistrict officers. Subdistrict officers, in turn, authorize MGNREGS payments and manage frontline workers who implement program works. Our intervention start date varied by state: February 2017 for Madhya Pradesh and October 2017 for Jharkhand.

to use PayDash.

We report four sets of findings. First, Google Analytics data show local bureaucrats used PayDash to obtain program information. The halving of PayDash usage during a month-long unexpected data outage, which disabled access to up-to-date payment processing information while leaving other app functionality intact, indicates that officials used PayDash to gain real-time implementation information. Usage levels recovered once the data outage was resolved.

Second, data from 17.4 million worker attendance registers spanning the intervention and preceding year shows that bureaucrats in PayDash districts process worker payments 17% (1.4 days) faster on average and with less variability than in control districts. While PayDash only provided payment processing information, we observe increased work provision in PayDash districts: Participating households increase monthly days worked by 10%, leading to 1,700 more person-days worked per subdistrict-month. Work activity impacts, including a 23% increase in active worksites, are concentrated during the MGNREGS high season, when agricultural job options are limited. We find evidence supporting improved bureaucratic bandwidth, as discussed below, and citizens' demand for work as influencing pathways.

Third, we show evidence that the reduction of managerial information acquisition costs was a primary channel of PayDash impact. Specifically, if these costs constrain implementation, PayDash provision at the principal and manager levels should be substitutes. If managers instead use information to collude with frontline workers and extract rents, program improvements will occur only if principals are given PayDash. Using experimental variation in who received PayDash, we show that MGNREGS performance impacts are statistically indistinguishable by level of bureaucratic hierarchy treated, and no additional gains are achieved when PayDash is given to both levels – demonstrating substitutability in PayDash access. Furthermore, we use quasi-exogenous variation in the number of local units overseen by subdistrict officers to show that PayDash-driven payment processing gains are concentrated in high-workload districts where easier access to information is likely to be especially valuable in improving bureaucratic bandwidth. Processing time reductions are nearly twice as large in districts above median (22%) compared to below median (12%) in terms of number of local units per subdistrict.

Our final set of findings relates to bureaucrat outcomes. District supervisors often incentivize subdistrict officer performance via bureaucratic posting transfers. Changing posts is typically costly for subdistrict officers, and can also be detrimental to program implementation. Stronger knowledge of subdistrict officer actions should allow supervisors to better condition moves on officer effort, rather than program outcomes. For instance, understanding whether payment delays reflect frontline issues outside an officer's control or the officer herself delaying invoice submissions allows a supervisor to transfer the officer out of her position solely in the latter scenario. PayDash reduces subdistrict transfers by 11 percentage points (24%), but only when the district supervisor receives PayDash. Endline surveys show that PayDash improves subdistrict officers' accuracy in judging payment processing performance by 19%, which aligns with informational gains from the platform. Effects are similar across treatment arms, and supervisors report sharing PayDash data with their subdistrict subordinates. Audit data provides additional evidence against the rent-seeking channel: we observe no PayDash impact on program implementation irregularities, including financial misappropriation.

PayDash is a cost-effective way of enhancing state capacity. We compare PayDash costs to the primary alternative for reducing payment processing time: additional staffing. To achieve the same processing time improvement as PayDash, study locations would need to hire more than five officers per subdistrict. While adding staff is cost effective, it is dominated by PayDash, whose benefits come at 1% of additional staffing costs in the first year, with further cost reductions in subsequent years. We also compute the benefit–cost ratio in which, given the right-to-employment framework, we center on two citizen benefits: averted consumption loans and improved MGNREGS work access. Our back-of-the-envelope estimates show that benefits outweigh platform development and maintenance costs by more than 170 times in the first year. In subsequent years, when development costs are significantly lower, the benefits exceed annual maintenance cost by roughly 630 times.

Our paper contributes to multiple literatures. Research on e-governance reforms for MGNREGS has shown that reductions in administrator responsibilities during payment-related processes, including funds flow approval (Banerjee et al. 2020) and payment delivery (Muralidharan et al. 2016), lower funds leakage. This work also finds that citizen-facing reforms improve work-related outcomes, but eliminating administrative responsibilities for funds flow does not. Our contribution is to show that a digital intervention that lowers information frictions for bureaucrats can improve implementation even while holding organizational structure constant.

The broader literature on how information frictions impact service delivery in lower-income countries has largely focused on top-down monitoring for disciplining government workers (Banerjee et al. 2008; Duflo et al. 2012; Dhaliwal and Hanna 2017; Finan et al. 2017). More recent research emphasizes the importance of information for managers (Dal Bó et al. 2021).[4] Our contribution to these literatures is an experimental comparison of the implications of improving information access at different bureaucratic levels.[5]

In demonstrating that reducing bureaucrats' information acquisition costs is particularly beneficial in higher workload areas, we link to a literature that shows under-resourcing is common in lower-income countries' administrative contexts and harms program implementation (Rogger 2017; Dasgupta and Kapur 2020; Aman-Rana et al. 2023). Finally, we contribute to a body of work on how government digitization can reduce information frictions and boost bureaucratic productivity (Callen et al. 2020; Carrillo et al. 2024; Mattsson 2024) or backfire and harm performance by weakening incentives to comply with program requirements (Aman-Rana and Minaudier 2024).

The paper is organized as follows: Section 2 provides context and a simple conceptual framework to motivate the experimental design. Section 3 describes data, bureaucrat PayDash engagement, and the empirical approach. Section 4 presents PayDash impacts, Section 5 conducts benefit-cost analysis, and Section 6 concludes.

# 2 Context and Experimental Design

MGNREGS pays rural households for manual labor on infrastructure projects. In this section, we first describe MGNREGS administration and implementation challenges. We then

[4]See also Fenizia (2022) and Best et al. (2023), who provide evidence on the relevance of manager talent and effectiveness, respectively, to public sector productivity.

[5]Our results align with research that points to information gains from greater autonomy for middle-tier bureaucrats outweighing corruption concerns in relation to bureaucratic performance (Rasul and Rogger 2018; Bandiera et al. 2021; Rasul et al. 2021). Also see Deserranno et al. (2024), who consider the role of managers beyond monitoring in multi-layered organizations.

describe the PayDash intervention, develop a conceptual framework to identify how PayDash availability impacts MGNREGS outcomes, and detail the experimental design.

## 2.1 MGNREGS Implementation

### A. Administrative Structure

MGNREGS is administered through a district-based bureaucracy including district, subdistrict (block), and frontline (Gram Panchayat, or GP) officers.[6] Annually, district supervisors approve a list of MGNREGS projects (the "shelf of works") for implementation in each GP. To open project worksites, publicize work opportunities, and allocate jobs, GP officers collaborate with the subdistrict MGNREGS officer, the program officer (PO), who reports to the subdistrict Chief Executive Officer (CEO).[7] The number of active worksites is countercyclical to agricultural activity during the year (Imbert and Papp 2015). A typical workspell at a worksite lasts six days, after which a GP agent, the Gram Rozgar Sevak (GRS), enters worker information into an attendance register (muster roll). This marks the start of Stage I of payment processing for the register.

Stage I involves multiple steps: First, at the GP level, the GRS records attendance in the digital MGNREGS Management Information System (MIS). Next, an engineer verifies the associated work and the GRS enters work details into the MIS. Following this, the logged data is reviewed at the subdistrict level, and a worker payroll and associated funds transfer order (FTO) are generated for PO approval. Once the subdistrict digitally authorizes the FTO, Stage I of payment processing is complete. These steps should be completed within eight days. District MGNREGS officers (now on, supervisors) have a purely supervisory role for Stage-I payment processing, and their administrative structure parallels the subdistrict level: the district PO oversees MGNREGS and reports to the district CEO.[8]

Following subdistrict authorization, the federal government's electronic funds management system routes payment requests to banks that deposit funds into workers' accounts. Stage II of payment processing is largely automated and should be completed within seven

[6] Appendix Figure A1 provides an organizational chart.

[7] We use position titles from Madhya Pradesh, corresponding to the Assistant Program Officer (PO) and Development Commissioner (CEO) in Jharkhand.

[8] The position title corresponding to district CEO in Jharkhand is Development Officer.

days. If a payment transfer fails (typically due to incorrect identification or bank account details), a rejected request is flagged for the subdistrict office to correct and re-route to the bank.

Bureaucrats monitor work verification and payment processing via administrative data on the MGNREGS website.[9] The website landing page displays state-wise attendance register delays at each of the Stage-I processing steps. From there, bureaucrats navigate through pages with step-specific delayed register counts for districts, subdistricts, and GPs. Once at the list of GPs, they can access GP-by-step pages to view specific attendance registers. Bureaucrats discuss these statistics in person and via video conference and WhatsApp.

### B. Implementation Challenges

Payment delays and insufficient work provision are critical and interlinked MGNREGS implementation issues. The requirement that Stage-I worker payment processing be completed within eight days of a workspell is routinely violated. In the year before PayDash rollout, monthly Stage-I wage processing in our study states averaged 18 days, with 85% of subdistrict-month averages exceeding the eight-day threshold (Appendix Figure A2). On average, an additional day of Stage-I processing time was associated with an additional 0.94 days for wages to reach workers. Similarly, worker demand typically exceeds available jobs (Desai et al. 2015; Zimmermann 2021; Azim Premji University 2022).

At baseline, subdistrict officers ranked payment delays as the second most significant worker concern, after low program wages (Figure 1a). They related citizen work interest to payment delivery speed, ranking "inadequate demand registration due to...low motivation and payment delays" as the second highest implementation challenge (Figure 1b). When asked to rank performance metrics for subdistrict officers, supervisors prioritized work provision followed by payment delays (Figure 1c). Supervisors base performance incentives on MIS-reported program outcomes. Because wages are contractually fixed, performance incentives typically take the form of certificates for good performance, written reprimands, and, in extreme cases, show cause notices for poor performance. Bureaucratic posting transfers are widely used; 77% of district supervisors stated having transferred subordinates for

[9] "R14.3 Dashboard for Delay Monitoring System". Appendix Figure A3 provides example screenshots.

performance (Appendix Table A1).

Stage-I payment processing delays are caused by delayed engineer visits to measure worksite progress, slow MIS data entry by GP agents, and subdistrict officer delays in reviewing submitted materials and signing FTOs. Limited manager bandwidth, reflecting under-resourcing and heavy workloads, weakens both monitoring and coordination activities within the bureaucracy (Dasgupta and Kapur 2020). In baseline surveys, subdistrict officers report typically working over 70 hours per week and having more than 40 work-related calls daily (Appendix Table A1); 30% confirm having an "additional charge", i.e., temporarily covering a vacancy in another position. Likely reflecting high workload, 26% of subdistrict officers report not being in regular (weekly) contact with frontline agents in any of the GPs under their purview.

Poor IT infrastructure increases workloads. Subdistrict officers rank "infrastructural issues such as poor internet connectivity and power shortages" as their top implementation challenge (Figure 1b). Our study-design phase included semi-structured interviews with officers who described how these issues made using MGNREGS website data to monitor payment processing more time consuming. The average subdistrict bureaucrat visits hundreds of landing pages to view information about her jurisdiction.[10] Exporting and reformatting information to meet officers' needs (e.g., comparing performance across subordinates or over time) requires additional effort, and web connectivity problems add further delays.

Rent extraction by bureaucrats may also worsen MGNREGS implementation by displacing bandwidth from other duties or directly impacting program performance (e.g., they may delay payment processing as a bargaining tactic).[11] In over 4,800 audits conducted in control area GPs by external government units between October 2017 and March 2020, financial misappropriation was detected in 10% of GPs. Frontline workers may seek bribes to provide jobs or to collude with villagers to list them as workers without requiring work, while subdistrict officers can use their sign-off powers to extract rents from frontline workers. Consistent with rent extraction being concentrated at lower levels, control-GP audits were

[10] Each page corresponds to a GP-by-processing-step, subdistrict officers manage more than 45 GPs on average, and Stage I consists of five steps.

[11] Bureaucrats minimized the importance of corruption in affecting MGNREGS implementation (Figure 1), but this could reflect self-serving biases.

more likely to identify any concerns involving GP (13%) or subdistrict (2%), as compared to district (0.02%), officers. Financial misappropriation was involved in officer-related GP- and subdistrict-level issues in 21% and 40% of reported cases, respectively.

In this setting, the returns to technology-based solutions that help bureaucrats obtain implementation data depend on the relative importance of effort costs versus agency concerns. PayDash, the technological innovation we evaluate, is described below, and we use a simple framework to identify how bureaucratic incentives and the administrative level of PayDash provision influence PayDash's impact on program performance.

## 2.2 The PayDash Platform

We collaborated with India's Ministry of Rural Development to develop a mobile- and web-based app, PayDash, which reduces effort costs of accessing and sharing MGNREGS worker payment processing information. PayDash relies on automatic timestamps generated as bureaucrats use the MIS to complete work verification and payment processing steps for each attendance register, eliminating accuracy concerns related to user-provided data. Bureaucrats log in for daily-updated information for their jurisdiction. The PayDash mobile app is robust to intermittent connectivity, allowing those in locations with poor internet and mobile coverage to view information from their last online-connected session.

We tailored PayDash by administrative level. Delayed attendance register numbers are updated daily on the subdistrict version's homescreen. Users can access disaggregated information from there by clicking through separate "cards" for specific GP-by-subordinate pairs. Each card displays the number of attendance registers delayed at steps for which the subordinate officer is responsible, together with identifying information and register-specific details including extent of delay. Appendix Figure A4 presents example mobile-app homescreen and card screenshots. From each card, a user can call or send a WhatsApp message to her subordinate, whose location and contact number are pre-loaded into the app during onboarding. The WhatsApp message functionality also allows the user to include pre-filled delayed register details from the card. Finally, a performance dashboard displays charts of subdistrict and GP-specific historical processing times, both step-specific and overall.

The district version of PayDash is similarly structured, with the homescreen displaying district statistics and subdistrict cards. Each card reports the number of delayed attendance registers and average length of delay, overall and per step, and includes contact icons for relevant subdistrict officers. The district performance dashboard displays district and subdistrict-specific charts, and is otherwise designed identically to the subdistrict version.

## 2.3 Conceptual Framework

We use a stylized example to demonstrate how impacts of PayDash vary with managerial incentives and the administrative level at which PayDash is provided.

Assume MGNREGS wage payments are managed by a principal $P$ (district officer) and a manager $M$ (subdistrict officer).[12] The manager chooses effort level $e_M \in \{0, 1\}$ at cost

$$c(e_M) = \begin{cases} 0, & e_M = 0 \\ c_M > 0, & e_M = 1 \end{cases}.$$

The realization of output $Y$ is random and depends on $e_M$:

$$Y(e_M) = \begin{cases} Y_1 > 0 & \text{with probability} \quad \pi_{e_M} \\ 0 & \text{with probability} \quad 1 - \pi_{e_M} \end{cases},$$

where $0 < \pi_0 < \pi_1 < 1$. That is, $Y$ is larger with higher probability when $e_M = 1$. We interpret higher output as improved program implementation, resulting in quicker worker payment processing and gains in other dimensions such as work provision.

The principal chooses between two incentive contracts: $I \in \{L, H\}$. A general way of modeling these contracts is in terms of wage payment $w_I$ from $P$ to $M$. In the high-powered contract $H$, $w_H$ is conditioned on output $Y$, while contract $L$ conditions wages $w_L$ on effort $e_M$ and entails effort cost of monitoring, $c_P > 0$, for the principal. In sum,

$$w_H = w_H(Y) = \begin{cases} w_0, & Y = 0 \\ w_1, & Y = Y_1 \end{cases} \quad \text{and} \quad w_L = w_L(e_M) = \begin{cases} \underline{w}, & e_M = 0 \\ \bar{w}, & e_M = 1 \end{cases}.$$

We impose a limited liability constraint, so $w_H, w_L \in [0, Y]$.

In our context, the principal influences incentives not through wages but by transferring

[12] As PayDash was provided only at these two levels, we suppress the frontline agent level.

a poorly performing manager to another post. We define bureaucratic post transfers as realizations of low wages $w_0$ and $\underline{w}$. Letting $t_I$ denote the transfer choice under contract $I$,

$$t_H = t_H(Y) = \begin{cases} 1, & Y = 0 \\ 0, & Y = Y_1 \end{cases} \quad \text{and} \quad t_L = t_L(e_M) = \begin{cases} 1, & e_M = 0 \\ 0, & e_M = 1 \end{cases}.$$

Then, the expected transfer under contract $H$ (characterized by $w_H$) is given by

$$\mathbb{E}[t_H|w_H] = \mathbb{P}[Y = 0|w_H].$$

Transfer under contract $L$ (characterized by $w_L$) is explicitly determined by manager effort.

Principal and manager are risk neutral with utilities denoted by $U_{P,I}$ and $U_{M,I}$, respectively, under contract $I \in \{H, L\}$. Normalizing the manager's outside option payoff to 0, the principal's maximization problem under contract $H$ is:

$$\begin{aligned} \max_{w_0,\, w_1} \quad & \pi_{e_M}(Y_1 - w_1) - (1 - \pi_{e_M})w_0 \\ \text{s.t.} \quad & e_M \in \underset{e}{\operatorname{argmax}} \quad \pi_e w_1 + (1 - \pi_e)w_0 - c(e) \quad && (IC_H) \\ & \pi_{e_M} w_1 + (1 - \pi_{e_M})w_0 - c(e_M) \geq 0 && (IR_H) \\ & w_0, w_1 \in [0, Y] && (LL_H) \end{aligned}$$

The principal's maximization problem under contract $L$ is:

$$\begin{aligned} \max_{\underline{w},\, \bar{w}} \quad & \pi_{e_M}(Y_1 - \bar{w}) - (1 - \pi_{e_M})\underline{w} - c_P \\ \text{s.t.} \quad & e_M \in \underset{e}{\operatorname{argmax}} \quad \mathbf{1}_{e=1}\bar{w} + \mathbf{1}_{e=0}\underline{w} - c(e) \quad && (IC_L) \\ & w_L(e_M) - c(e_M) \geq 0 && (IR_L) \\ & \underline{w}, \bar{w} \in [0, Y] && (LL_L) \end{aligned}$$

The timing of the game is:

1. $P$ writes incentive contract $I \in \{H, L\}$ subject to cost $c_P$ for contract $L$.

2. $M$ chooses to accept or reject the contract. If accept, $M$ chooses $e_M$. If reject, both $M$ and $P$ receive payoff 0 and the game ends.

3. $Y$ is realized, the incentive contract is implemented, and payoffs are allocated.

Appendix B characterizes the solution to the principal's optimization problem, including for an extension where the manager is additionally motivated by rent-seeking considerations. In that extension, a rent-seeking manager is modeled as one who directly benefits from choosing $e_M = 0$. This is a reduced form way of capturing collusion wherein the manager commits to not monitoring frontline agents in return for some payment.

Consider a status quo with high enough $c_M$ and $c_P$, so that the principal chooses contract $H$ and the manager sets $e_M = 0$. The impacts of introducing PayDash are as follows:

1. *Absent managerial rent-seeking, if PayDash sufficiently lowers $c_P$ and $c_M$ when provided to the principal and manager, respectively, implementation improves under access at either or both levels – i.e., manager and principal PayDash are substitutes.*

2. *With managerial rent-seeking, providing PayDash to the principal is necessary to improve implementation.*

3. *Regardless of managerial rent-seeking, PayDash provision involving the principal reduces expected transfers by (weakly) more than if the manager alone receives PayDash.*

Appendix B provides details on these results, and the intuition is as follows. Absent managerial rent seeking, a PayDash-induced reduction in $c_P$ causes the principal to switch from $H$ to $L$ contract and the manager to exert greater effort.[13] If only $c_M$ is reduced, the manager increases effort but the contract remains $H$. With reductions in both $c_P$ and $c_M$, the principal's choice of contract depends on the relative magnitudes of cost reductions, but manager effort increases regardless. With a rent-seeking manager, manager-only PayDash access will not increase her effort since she benefits from $e_M = 0$. In contrast, as long as the manager's rent-seeking returns are not too high, PayDash access for the principal will lead her to choose contract $L$ and the manager to exert high effort, improving implementation. Irrespective of managerial rent-seeking, PayDash to the principal switches the contract type to $L$ and lowers expected transfers, since under contract $H$ low output remains a non-zero probability event. We now describe the experimental design that enables us to test these predictions.

[13] An additional potential channel of impact from principal PayDash access is information sharing with the manager, which reduces $c_M$.

## 2.4 Experimental Design

In the two North Indian states of Madhya Pradesh and Jharkhand, we randomly assigned 73 districts, containing 561 subdistricts, to one of four groups: 17 districts where district supervisors received PayDash ("district only"), 16 where subdistrict officers received PayDash ("subdistrict only"), 20 where both district supervisors and subdistrict officers received PayDash ("combination"), and 20 without PayDash ("control").[14] CEOs and POs at each treated administrative level were given PayDash. We launched PayDash across Madhya Pradesh in February and March 2017 and in Jharkhand in October 2017. The intervention ended in August 2018, to avoid officer deputations and transfers in anticipation of the November 2018 Madhya Pradesh elections.

As part of rollout, we conducted 177 district-based, half-day sessions to administer baseline surveys and conduct training. Control and treatment bureaucrats were assigned to different sessions, as were subdistrict and district bureaucrats. All bureaucrats, regardless of treatment assignment, were surveyed at session start and received "refresher" training on MIS tools to access MGNREGS information through the program website. Training sessions for treated bureaucrats lasted an additional hour, during which they installed the PayDash smartphone app and were taught how to use the tool.[15] Bureaucrats who attended training sessions completed a baseline survey, and individual training was provided to those who missed the initial sessions.[16] We contacted each district at multiple points during the intervention to identify position changes and adjust PayDash access.[17] Newly appointed bureaucrats in treatment areas were trained and provided PayDash. Bureaucrats transferred between treated areas had PayDash region-specific access updated, while those exiting treated areas had their login deactivated.

[14]The experimental sample excludes one pilot district per state. Randomization was stratified in each state by average attendance-register-by-worker payment time and average subdistrict volume of person-days worked within the April 2015 to June 2016 range. Appendix Section C.1 provides variable construction details. Treatments were assigned in roughly equal proportion across 50 Madhya Pradesh districts; and roughly one-third each to control and combination and one-sixth each to district and subdistrict only across 23 Jharkhand districts.

[15]Appendix Section C.2 provides additional training session details.

[16]For 1,184 (93%) of 1,270 total district and subdistrict CEO and PO positions, an officer attended a training session. The large majority of the training coverage gap reflected vacant positions. Training participation and baseline survey completion did not significantly differ with treatment status.

[17]At 1, 6, 13, & 17 months in Madhya Pradesh; and 1, 6, & 10 months in Jharkhand, given later rollout.

# 3 Data, PayDash Usage, and Empirical Strategy

## 3.1 Data Sources

**PayDash usage data:** Google Analytics data provides usage measures: session counts, usage duration, and WhatsApp messages and calls initiated from PayDash.[18]

**Administrative data:** We use data from the 17.4 million worker attendance registers issued in Jharkhand and Madhya Pradesh from September 2016 to August 2018. For each register, we use the workspell dates and subdistrict office payment request submission date to determine duration of Stage-I payment processing. We assign each register to the month in which the associated workspell ended and Stage-I processing began, and calculate subdistrict-month-level processing time measures and number of attendance registers. We also use administrative data to construct subdistrict-month-level measures of work by MGNREGS participants, active worksites, and share of payment requests rejected at Stage-II bank routing.[19] For all non-categorical measures, we bottom/top code values at the 1st/99th percentiles of the control distribution.

To assess MGNREGS implementation quality and community demand for work, we utilize data from social audits, GP-level exercises conducted by government auditors external to communities. Appendix C.3 provides details on social audit procedures. Approximately 70% of sample GPs experienced an audit covering some range of the intervention period, with coverage balanced across treatment arms.

**Bureaucrat survey and transfer data:** Baseline bureaucrat surveys collected information on socio-demographic characteristics and the MGNREGS administrative environment. Between May and December of 2020, we conducted a follow-up phone survey with subdistrict and district POs in Madhya Pradesh, which provides us additional information on MGN-

[18]When a user interacts with PayDash and at least 30 minutes have lapsed without activity, or when an ongoing session continues into the next calendar day, a usage session is logged. Only the mobile app records usage duration, and we do not capture offline mobile-based usage.

[19]The data span the same time period as for processing data, with the exception of worksites data for Jharkhand which is available from April 2017 onward.

REGS administration and treated bureaucrats' use and perceptions of PayDash.[20] We gathered data from district offices on subdistrict officers' postings through phone-based tracking.

## 3.2 Summary Statistics and Balance

As shown in Panel A of Appendix Table A1, sample districts average 1.4 million residents and 7.7 subdistricts. GP number varies across subdistricts, with an average of 47 GPs. Over 300,000 person-days were worked through MGNREGS across 5,500 attendance registers in the average subdistrict in the year before the intervention, with an average Stage-I worker payment processing time of 17.7 days.

Panels B and C report baseline bureaucrat characteristics. The typical bureaucrat is mid-career, male, and college educated. Over 93% use the MGNREGS MIS everyday, and smartphone ownership is practically universal (not shown). High workloads are pervasive: bureaucrats at both levels work over 70 hours per week, with 44% of district supervisors and 30% of subdistrict officers reporting an additional charge. In addition, bureaucrats have limited program outcome knowledge: District supervisors had a 38% knowledge gap for payment delivery time, measured as the absolute difference between actual and perceived average time to payment in their district over the last year, divided by the actual value. Subdistrict officers had a 45% knowledge gap. Frequent subdistrict officer transfers likely contribute to their limited knowledge.

Our sample is well-balanced across treatment arms (Appendix Tables A1 and A2). Throughout, our analysis follows our pre-registered analysis plan (PAP). Appendix Table A3 lists and explains all plan deviations and extensions.

## 3.3 PayDash Usage

Table 1 reports position-month PayDash usage statistics for subdistrict and district bureaucrats (Panels A and B). Considering localities where a single level of the hierarchy received PayDash, the first row of each panel shows similar total use at the subdistrict and district levels in columns (1)–(4), with 4–5 sessions and 25–30 minutes of mobile-based interaction per month. Our measures are lower bounds since they do not capture mobile-based use in

[20]Our overall response rate is 77.1%, with insignificant differences by treatment.

offline mode and null usage is recorded for bureaucrats when they move until their PayDash access is updated. Appendix Table A4 shows total monthly use at each level averages approximately 12-13 sessions and 70 minutes of mobile-based engagement when we condition on positive usage.

Most PayDash engagement is by POs, who are solely tasked with MGNREGS management, rather than CEOs, who have a wider set responsibilities. Figure 2 shows stable usage patterns over time. Columns (5) and (6) of Table 1 report the number of calls and WhatsApp messages sent via the in-app contact feature. Districts use this functionality more than subdistricts, possibly reflecting a greater share of remote supervision and communication with lower-level bureaucrats. Fewer than 5% of PayDash sessions occur through the web-based interface (not shown), indicating bureaucrats value the mobile-tailored presentation and offline data availability of the mobile-app interface.

We next consider whether PayDash use at a given bureaucrat level is impacted by platform access for the other level. The second row in each panel of Table 1 reports results from regressions of the usage measures on an indicator for PayDash access at both officer levels, where month and strata fixed effects are also included and the sample is the set of locality-months in which bureaucrats at a given level received PayDash (regardless of provision at the other level). Panel A shows similar subdistrict PO usage irrespective of whether district supervisors also have access. In Panel B, we see that District POs use PayDash less when their subordinates have platform access, though the differences are noisily estimated.

Finally, a brief platform shock lets us assess bureaucrats' value of real-time information. In July 2017, a central-government server outage shut down PayDash's attendance register API for most of the month, preventing the platform from updating information on delayed attendance registers. The in-app contact and historical performance features remained functional. Table 2 examines the outage impact in Madhya Pradesh, as the PayDash rollout in Jharkhand occurred after the outage. In odd columns, we regress locality-month measures of bureaucrat usage on an outage month indicator and locality fixed effects, restricting to periods within three months of the outage. In even columns, we replace the outage month indicator with pre- and post-outage indicators. Consistent with bureaucrats valuing the real-time processing status information, subdistrict and district PayDash usage dropped by more than half during the data outage but recovered after the real-time information was restored.

### 3.4 Empirical Approach

Our analysis plan for MGNREGS administrative data specified panel regressions where we include pre-intervention data to improve the precision of estimated impacts. In Section 4.1, we assess the impacts of PayDash access at any officer level, estimating treatment effects on outcome $Y_{sdt}$ for subdistrict $s$ in district $d$ using monthly data:

$$Y_{sdt} = \beta T_{dt} + \alpha_{sd} + \alpha_t + X'_{dt}\theta + \varepsilon_{sdt}. \tag{1}$$

$T_{dt}$ is a pooled treatment provision ("Any PayDash") indicator, $\alpha_{sd}$ and $\alpha_t$ are subdistrict and month fixed effects, and district-specific controls, $X_{dt}$, account for linear time trends. Standard errors are clustered by district. The analysis sample spans September 2016 to August 2018, with the intervention occurring between February 2017 and August 2018.[21]

To consider the dynamics of PayDash impacts, we use an event study specification:

$$Y_{sdt} = \sum_{\substack{-5\leq\tau\leq 8,\\ \tau\neq -1}} \beta_\tau T_{\tau,dt} + \alpha_{sd} + \alpha_t + X'_{dt}\theta + \varepsilon_{sdt}. \tag{2}$$

$T_{\tau,dt}$ is an indicator variable for whether month $t$ in district $d$ falls $\tau$ months relative to the provision of PayDash, where $\tau = -5$ captures periods five or more months prior and $\tau = 8$ all periods eight months and beyond.

We also examine in Section 4.1 how treatment impacts vary with seasonality in agricultural activity by adding an MGNREGS high-season indicator and its interaction with the PayDash indicator to Equation (1).[22] Similarly, in Section 4.3, we include interactions of PayDash provision and time-invariant measures of administrative structure to assess heterogeneity in treatment effects by bureaucrats' administrative environment. When considering

[21]Our OLS estimates provide intent-to-treat effects in a setting marked by interruptions in PayDash availability, including the temporary data outage and position-specific interruptions due to lags between bureaucrat movement and updating of PayDash access following transfers tracking rounds discussed in Section 3.3.

[22]MGNREGS work provision is concentrated in the four pre-monsoon late spring and summer months, effectively maximizing social protection when agricultural work is scarce. The high seasons in Jharkhand and Madhya Pradesh are April-July and May-August, respectively. In control GPs, the monthly volume of days worked during high season was 78% higher than in other months over the evaluation period.

bureaucrat and audit outcomes with a single post-rollout measure in Section 4.4, we regress each outcome of interest on a treatment indicator and randomization strata fixed effects.

In Sections 4.2 and 4.4, we evaluate impacts of the different treatment arms, replacing the pooled treatment provision indicator in Equation (1) with indicators for District Only PayDash ($TD_{dt}$), Subdistrict Only PayDash ($TS_{dt}$), and Combination PayDash ($TC_{dt}$):

$$Y_{sdt} = \beta_1 TD_{dt} + \beta_2 TS_{dt} + \beta_3 TC_{dt} + \alpha_{sd} + \alpha_t + X'_{dt}\theta + \varepsilon_{sdt}. \tag{3}$$

This specification evaluates district- and subdistrict-level PayDash provision, and allows us to test for their substitutability (against $H_0 : \beta_3 = \beta_1 + \beta_2$). When analyzing heterogeneity in PayDash impacts or the effects on cross-sectional measures separately by treatment arm, we replace the pooled treatment indicator with treatment arm indicators in corresponding specifications.

Our analysis plan registered the use of generalized difference-in-differences (two-way fixed-effects) estimators using administrative panel data. However, with potential heterogeneity in treatment effects over time and the staggered rollout of PayDash within and across states, a recent literature highlights concerns of potential bias in treatment effect estimates based on approaches such as Equations (1) and (2) (see, e.g., de Chaisemartin and D'Haultfoeuille (2023) for a survey). In our subsequent analysis, we consider robustness of our MGNREGS administrative data outcomes to using alternative heterogeneity-robust estimators (Callaway and Sant'Anna 2021; Sun and Abraham 2021; de Chaisemartin and D'Haultfoeuille 2024).

# 4 Impacts of PayDash

We first examine effects of PayDash on MGNREGS outcomes. Next we use experimental variation in the bureaucratic level receiving PayDash to assess substitutability, and pre-existing variation in district administrative structure to evaluate how effects differ with bureaucrat workload. We then examine impacts on bureaucrat and citizen outcomes.

## 4.1 Effects on Payment Processing and Program Scale

### A. Visual Evidence

Figure 3 plots estimates from regressions of the form described in Equation (1), where the outcomes considered are the shares of attendance registers processed within different Stage-I time ranges. The leftmost bin shows a 9.3 percentage point (23%) increase in the probability that payment processing was not "late", i.e., completed beyond the eight-day regulatory maximum. Looking across time-range bins, we see that PayDash caused a general leftward shift in the processing time distribution, with declines in the shares of attendance registers processed over longer time ranges, including beyond 32 days.

Based on Equation (2), Panel A of Figure 4 displays the event study plot of PayDash's impact on log payment processing time. Improvements in processing times manifest within a few months and persist through the evaluation period.[23] Panel B examines effects on the intensity of household MGNREGS participation. Similar to payment processing, the impact of PayDash on log days worked per participating household strengthens gradually over the course of a few months. These participation impacts likely reflect a mix of increasing worker demand in response to improved program implementation (e.g., faster payment processing) and reduced rationing as bureaucrats increase worksites.[24] Appendix Figure A5 shows similar dynamics when we use alternative estimators, and Appendix Figure A6 shows consistent patterns when studying impacts separately by treatment arm.

### B. Regression Estimates

Table 3 presents estimates from two specifications for PayDash's impact on wage processing and work outcomes. Panel A reports average treatment impacts (Equation (1)), while Panel B examines the seasonality of treatment effects. Columns (1)–(4) consider wage processing outcomes. Panel A shows that PayDash provision lowered Stage-I processing time by 17% (18.1 log points; column (1)).[25] This translates into an average reduction of 1.4 days. Con-

[23] The gradual improvement in processing times may reflect time needed to identify and address performance issues and to clear the stock of delayed attendance registers from previous periods.

[24] Greater bureaucrat effort in publicizing available work may also be relevant (Gulzar and Pasquale 2017).

[25] The relationship holds when excluding controls (Appendix Table A5), using alternative estimators (Appendix Table A5), weighting by number of attendance registers (Appendix Table A6) considering processing times in levels (Appendix Table A7), and inverse propensity weighting (Appendix Table A8).

sequently, the share of registers processed "late" decreased (column (2)). Improved payment processing speeds reduced variability, measured as the average absolute deviation of processing time from the subdistrict-month median, by 0.6 days (13%; column (3)). Panel B shows that the processing time impacts of PayDash weaken slightly but remain significant during the MGNREGS high season, likely due to the large increase in work volume and associated processing during this period.

We next consider the likelihood of worker payment requests being rejected after Stage-I processing, as measured by payment rejection rates across wagelists (groupings of attendance registers for which payment requests are jointly submitted). Rejections often reflect bureaucrats entering invalid recipient bank or individual identifying information into the MGNREGS system.[26] If PayDash causes bureaucrats to reduce processing time at the expense of work quality, rejection rates may increase. However, if PayDash frees up time for bureaucrats to allocate to these tasks or makes it easier for them to monitor and ensure worker details are correct, rejections may decrease. Column (4) shows PayDash caused a one-percentage-point reduction in rejection rates, with indistinguishable impacts across seasons. Another potential concern is that bureaucrats improved payment processing by reducing the number of attendance registers, possibly by extending workspell length and hence worker payment cycles. Appendix Table A7 shows that PayDash access did not reduce the number of registers processed or increase workspell length.

Columns (5)–(8) of Table 3 present treatment effects for MGNREGS participation outcomes. PayDash access led to a 10% increase in monthly work days for participating households, with similar increases observed in high and low seasons (column (5)). In contrast, the impact on total working households varies by season, with a positive though insignificant total high-season effect (column (6)). This seasonal pattern holds for total days worked, with a 14% total increase in the high season, significantly larger than the insignificant low-season gain (column (7)).[27]

How was the increased MGNREGS participation achieved? Our outcome of interest in

[26] After payment rejections, a subdistrict officer can try to address the source problems and re-submit payment requests. This requires coordination with frontline workers, potentially increasing delays.

[27] Appendix Table A7 shows that PayDash increased the share of below poverty line participants by 0.3 percentage points (2%) in the low season, but across seasons left female participation unchanged.

column (8) is the monthly number of active worksites. In control subdistricts, this value increases on average from 377 in low season to 533 during the peak season. PayDash caused a 23% overall increase in active worksites, driven particularly during the high season when worksite availability is typically a binding constraint. The timing of worksite expansion suggests it was a key mechanism driving the PayDash-induced increase in total days worked through MGNREGS. We consider the role of citizen demand for program work in Section 4.4.

Finally, in Appendix Table A9, we examine whether the impacts of PayDash diminished during the real-time data outage, when bureaucrats' use of the platform fell. If PayDash primarily helps bureaucrats identify consistently poorer versus better performing subordinates, a pause in real-time processing data after multiple months of full platform functionality may not impact program performance. We observe, however, that PayDash-driven improvements in payment processing were roughly 40% smaller during the data outage. This suggests that an important part of PayDash's value is facilitating the ongoing use of real-time attendance register information to prevent problems or better troubleshoot them as they arise.

## 4.2 Substitutability Across Bureaucratic Levels

Random variation in which bureaucrats received PayDash allows us to examine substitutability in PayDash provision across two levels of the bureaucratic hierarchy: district and subdistrict. Table 4 reports impacts on payment processing and work outcomes estimated separately by treatment arm (Equation (3)). As in the previous table, Panel A gives average impacts and Panel B considers differences between high and low season. For each regression in Panel A, we report the p-value from a test of the null hypothesis of equality between the sum of the impacts of district-only and subdistrict-only PayDash and the impact of providing PayDash at both levels. Rejecting equality, together with a smaller impact magnitude for combination PayDash provision, indicates substitutability in PayDash access across administrative levels. We also report the p-value from a test of the null hypothesis of equality in impacts across treatment arms.

Panel A shows that PayDash improved the processing time, household participation intensity, and worksite availability outcomes regardless of the level of bureaucratic hierarchy at which it was provided. Indicative of substitutability, for each of these outcomes, the impact of providing PayDash to both district supervisors and subdistrict officers is significantly smaller than the sum of the district-only and subdistrict-only effects. Further consistent with substitutability, PayDash did not have a larger impact when provided to both district supervisors and subdistrict officers as compared to either level alone. In Panel B, we observe similar seasonality patterns across treatment arms.

The evidence of substitutability, as interpreted through our conceptual framework, implies that PayDash impacts cannot be fully explained by better monitoring of rent-seeking subdistrict officers. In that case, performance benefits would only accrue if district supervisors had PayDash access. The substitutability of district- and subdistrict-level PayDash is instead consistent with subdistrict information constraints impeding program implementation – and PayDash for district supervisors leading to improvements through some combination of sharing information with subdistrict subordinates (thereby reducing effort costs of information collection for subdistrict officers) and better incentivizing effort by subdistrict officers (potentially by increased conditioning of performance incentives on their effort). We now turn to quasi-exogenous variation in bureaucratic workload to examine whether bureaucrats responsible for managing a larger number of subordinates, and so arguably having more limited bandwidth, benefit more from lower information acquisition costs.

## 4.3 Heterogeneity by Bureaucratic Workload

The geographic unit for implementing India's rural development programs after Independence was the subdistrict. Since their establishment was completed in 1964, subdistrict boundaries have remained fixed despite differences in population growth. In contrast, GPs were created by a 1993 constitutional amendment, with state-determined population thresholds. States use census data to adjust the number of GPs per subdistrict to remain consistent with these thresholds (Narasimhan and Weaver 2024).[28] Due to constant subdistrict borders and population-based GP definitions, subdistrict GP counts vary greatly. In our sample, subdistrict officers at the 25th percentile of the GP-per-subdistrict distribution manage 16

[28] The Madhya Pradesh GP population minimum is 1,000, with no explicit maximum. GPs in Jharkhand have a target population of 5,000. No subdistrict or GP boundary changes occurred during our evaluation period.

GPs, compared to 73 at the 75th. In comparison, 25th- and 75th-percentile districts in terms of subdistrict count contain 5 and 9 subdistricts, respectively. Appendix Table A10 shows a positive relationship between subdistrict officers managing more GPs and a baseline workload index including weekly hours worked, calls per work day, irregular local agent contact, and having an additional charge. In contrast, district supervisors' workload does not differ significantly with the number of subdistricts they oversee, likely reflecting the more limited variation in number of subdistricts across districts.

If PayDash improves MGNREGS outcomes by making it easier for subdistrict officers to obtain information, then under plausible assumptions those with heavier workloads should benefit more.[29] In Table 5, we examine heterogeneity in treatment impacts based on whether a district is above-state-median in terms of average GPs per subdistrict ("high GP-ratio").[30] Column (1) shows that PayDash reduced average processing times by 22% (25.1 log points) in high-GP-ratio districts, nearly double the improvement in low-GP-ratio districts. Columns (2) and (3) show that improvements in on-time processing and processing time variability are also stronger in high-GP-ratio districts, though the difference is noisily estimated for the latter.[31] Impacts on work volume outcomes do not differ by administrative structure, however. This suggests that in high-GP-ratio districts, PayDash's real-time information is particularly useful for monitoring a larger number of subordinates responsible for payment processing steps, rather than for creating additional work opportunities. The results are robust to including a host of treatment-interacted controls (Appendix Table A13) and using an overall-median-based measure of administrative structure (Appendix Table A14).

## 4.4 Impacts on Bureaucrat and Citizen Outcomes

### A. Posting Transfers

In our study context, bureaucratic posting choice is a prevalent performance incentive; 45% of subdistrict officers in control districts were transferred within six months of the intervention

[29] In our framework, we interpret greater workload as higher bureaucratic effort cost, which is consistent with the officer needing to gain information about more GPs. This implies lower expected effort in the status quo and larger performance gains with PayDash for sufficient effort cost reduction.

[30] Table A11 additionally reports heterogeneity by officer personality and cognitive characteristics.

[31] Appendix Table A12 presents results of treatment-arm-specific analysis.

rollout in each state. Our framework predicts that if PayDash lowers the principal's cost of acquiring information, then bureaucratic posting moves will become more responsive to managerial effort, and PayDash-induced increases in managerial effort will be accompanied by reduced transfer incidence.

Column (1) of Table 6 shows that district-only PayDash reduced the probability of subdistrict officer transfer within six months by 10.6 percentage points (24%). This impact is similar in magnitude to, and statistically indistinguishable from, the effect when both district and subdistrict levels receive PayDash ($p = 0.505$). These effects, however, are statistically distinguishable from the positively-signed impact of only subdistrict officers having platform access ($p = 0.012$ and 0.060, respectively). Additionally, consistent with district supervisors deciding subdistrict officer transfers, the sum of district and subdistrict PayDash impacts is similar to the impact of providing to both. Appendix Table A15 shows similar impacts over the longer time period of 17 months for Madhya Pradesh alone due to its earlier PayDash rollout, with PayDash reducing subdistrict transfers only when district supervisors receive platform access.

Section 4.2 shows similar performance improvements across treatment arms, but we observe reductions in transfers only when district supervisors have access to PayDash, indicating that improved district supervisor information about subdistrict performance is a key driver of the transfer impacts.

### B. Bureaucrat Knowledge and Citizen Demand

Our results point to PayDash lowering information frictions within the bureaucracy. We now use post-intervention surveys to directly examine PayDash's impact on subdistrict officers' program knowledge. We define a knowledge gap measure for subdistrict POs as the absolute difference between actual and perceived value of average time to payment in their subdistrict for the most recent fiscal year, divided by the actual value. Column (2) of Table 6 shows that PayDash reduced the average knowledge gap by 7.8 percentage points (19% of the control mean), with indistinguishable impacts across treatment arms.

Figure 5, based on post-intervention surveys, shows that 81% of district supervisors and 60% of subdistrict officers who received PayDash found it easier to learn about MGNREGS payment processing in their jurisdictions. In addition, 19% and 27% of district supervisors and subdistrict officers, respectively, report that PayDash helped them in gathering new information.[32] When asked how they used PayDash information, 68% of district supervisors reported sharing it with their subordinates, consistent with the similar subdistrict-level knowledge gap reductions across treatment arms. Additionally, 25% of district supervisors and 40% of subdistrict officers reported using PayDash to evaluate subordinate performance.

Next, we evaluate PayDash's impact on villagers' unmet demand for MGNREGS work. Our results show that PayDash-induced improvements in program implementation include increased work provision. This would reduce unmet work demand unless better program implementation, particularly faster payment processing, makes MGNREGS work more attractive, hence raising demand. To examine this, we construct a GP-level demand indicator based on social audit reports' documentation of villagers' unmet work demand.[33] Column (3) of Table 6 shows a 12.4-percentage-point higher probability of unmet demand in PayDash districts. This suggests that improved implementation enhanced workers' perceived value from participation, and consequently demand for MGNREGS work.

### C. Malfeasance

The evidence that PayDash impacts are similar irrespective of the level of bureaucracy receiving the app points against managerial rent-seeking primarily underlying weak program implementation. To gain direct evidence on this issue, we create an audit irregularity index from social audit reports. This includes indicators for GP-level issues in four categories: financial deviation (typically linked to poor record keeping; reported in 12% of control locations), financial misappropriation (including bribes, paying ghost workers, or other evidence of graft; reported in 10% of control areas), grievances raised (related to access to work, wages, etc.; reported in 14% of control areas), and other process violations (reported in 19% of control locations). Column (4) of Panel A in Table 6 shows that PayDash does not impact

[32] 94 and 75% of district and subdistrict POs, respectively, answered affirmatively to either information-related question. PayDash also encouraged bureaucrats to prioritize payment processing, as reported by 31% of district supervisors and 46% of subdistrict officers.

[33] Based on interactions with community residents, auditors record a response to the question, "Is there a demand for [MGNREGS] work that is not met?", with GP-level categorizations of "some", "a lot", or "none". Due to an 11-month audit reference period, we cannot evaluate seasonality in impacts on work demand.

the audit irregularity index.[34] In Panel B, we continue to see no statistically significant impacts by treatment arm, though the point estimates are suggestive of PayDash provision to subdistrict officers reducing audit irregularities. In columns (5)–(7), the outcomes of interest are indicators for the naming of GP, subdistrict, or district officers, respectively, in connection to audit-detected issues. GP officers are named the most often (13% in control GPs) and subdistrict officers are also mentioned, though rarely (2% in control GPs). In contrast, district supervisors are essentially never mentioned. Panel A shows no impacts of PayDash on these outcomes. In column (5) of Panel B, we see some noisily estimated indication that providing PayDash to subdistrict officers reduces GP-officer-related issues.

# 5 Benefit-Cost Analysis

India's 2005 National Rural Employment Guarantee Act established a justiciable "right to work". The year before our intervention, India's Supreme Court declared delayed MGNREGS worker wage payments "a clear constitutional breach committed by the State" (Supreme Court of India 2016). In this context, PayDash strengthened citizens' ability to exercise their right to paid work by causing quicker processing of worker payments and increasing the scale of MGNREGS activity. These observations motivate the scope and structure of our back-of-the-envelope benefit-cost analysis for PayDash in Table 7. We also consider whether the more traditional approach of adding government manpower may reduce payment delays as cost-effectively, if not more so.[35]

Following the citizen-centered perspective established by India's constitutional right to employment, we consider the value of the two primary benefits to rural households from PayDash's impact on MGNREGS performance, with Table 7 and Appendix C.5 providing additional details on the calculations in this section. First, we quantify the monetary benefit of quicker payments caused by PayDash. We assume faster payment times allow for fewer days of loan-financed household expenditure (and lower associated interest costs) needed to

[34] Appendix Table A16 further shows no significant treatment effects on the individual index components.

[35] Given the right-to-work framework, we do not benchmark against potential alternative uses of public funds in other domains. We also refrain from considering additional benefits related to the development of rural assets and broader economic impacts of workfare access, such as rural wage increases or other market changes (Imbert and Papp 2015; Muralidharan et al. 2023).

bridge the gap between workspell completion and payment arrival. This assumption reflects qualitative evidence that poor rural households awaiting slow and unpredictable MGNREGS payments commonly take out loans to support short-term consumption smoothing until wage payments arrive.[36] Based on estimated 1.3-day quicker payment delivery following a workspell, we assume loan size is reduced by an amount equal to one day of household consumption and that time to loan repayment drops by one day. Together with an assumed 34% annual simple interest rate, based on data from the 2019 All-India Debt and Investment Survey, and sixteen-day status quo repayment length, this yields $0.06 saved per loan. The observed monthly numbers of working households and workspells per household imply nearly 3,300 affected loans, with approximately $200 in interest avoided, per subdistrict-month.

Next, we assess the value of increased work days for households. PayDash led to roughly 1,700 additional person-workdays per subdistrict-month, providing more than $4,400 of wages to poor rural households. Scaling to the annual level across our two study states, Panel C shows annual benefits of approximately $1.4 million in interest costs avoided due to faster payment delivery and of nearly $31 million in additional wages due to greater workfare activity.

Panel B provides the costs associated with PayDash implementation and an additional staffing comparison scenario. Initial development and roll-out expenses for providing PayDash to relevant district and subdistrict bureaucrats at scale totaled approximately $136,000. Annual maintenance costs, including software updates, monitoring, and user access updates, sum to roughly $51,000. Second, we consider a plausible alternative approach to increasing MGNREGS implementation capacity in our study context: adding subdistrict-level staff. Based on the observed relationship between number of GPs overseen by subdistrict bureaucrats and payment processing times, we estimate an additional 5.3 bureaucrats needed per subdistrict to match the improvements in payment processing and program scale achieved by PayDash. Using baseline data on subdistrict PO salary and stipends for phone and data-related costs, we estimate a monthly cost of nearly $400 per bureaucrat. Panel C shows an at-scale cost of nearly $15 million per year from additional bureaucrat staffing.

In Panel D, we compare the benefit-cost ratios of PayDash provision and additional

[36]For example, survey and news reports highlight how MGNREGS workers facing delayed payments borrow from moneylenders at high interest rates to pay for food for their families (Barnagarwala 2022; Bhelari 2023).

staffing. Staffing expansion has benefits approximately twice hiring costs. In comparison, benefits from PayDash outweigh total development and maintenance costs by more than 170 times during the first year of implementation. In subsequent years, when no development costs are incurred, benefits outweigh costs by nearly 630 times. PayDash provision continues to compare favorably to staffing expansion when considering benefits related only to reductions in payment times. In this case, PayDash benefits are more than 7 and 27 times costs in the first and subsequent years, respectively, while staffing expansion benefits are less than one-tenth of associated costs annually.

# 6 Conclusion

This paper reports on a large field experiment that increased state capacity by providing bureaucrats in the MGNREGS administrative hierarchy with PayDash, a mobile- and web-based platform that made program implementation data easier to obtain. PayDash lowered payment processing times by 17% and increased work provision, especially during the agricultural lean season. These impacts occur regardless of the level of the bureaucratic hierarchy at which PayDash is provided, with no additional gains when given to both. This substitutability is at least partly due to district supervisors sharing PayDash information with their subdistrict subordinates. Supervisor access to PayDash reduced subdistrict posting transfers by 24%, indicating reduced reliance on blunt outcome-based performance incentives. Finally, government audits revealed that program performance gains occurred without an increase in local corruption.

Our study's results have encouraged other Indian state governments to request PayDash access, and the federal government is considering PayDash integration into the suite of digital tools available to regional bureaucrats. Doing so promises to be highly cost effective: Household benefits from PayDash were more than 170 times the cost of the platform in the first year alone. Additionally, PayDash costs would be roughly 1% those of hiring additional staff to similarly improve MGNREGS performance in the first year, and less in subsequent years. Overall, our findings demonstrate the value of digital tools in providing real-time information to overburdened bureaucrats tasked with delivering social protection programs in low-capacity environments.

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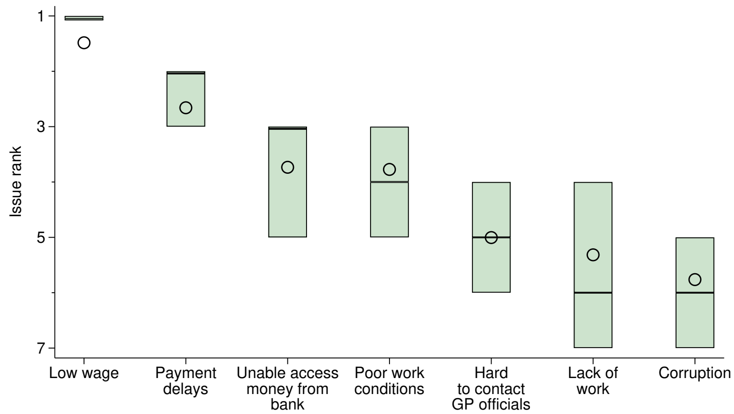
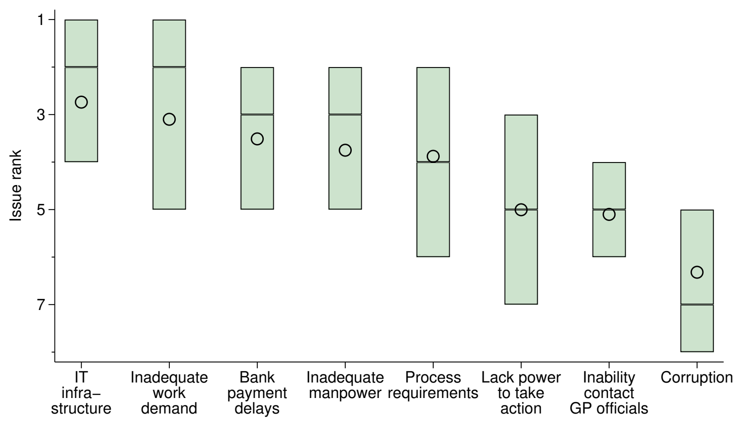
# Figures and Tables

Figure 1: MGNREGS Environment for Subdistrict Officers

(a) Worker Challenges - Subdistrict Reported



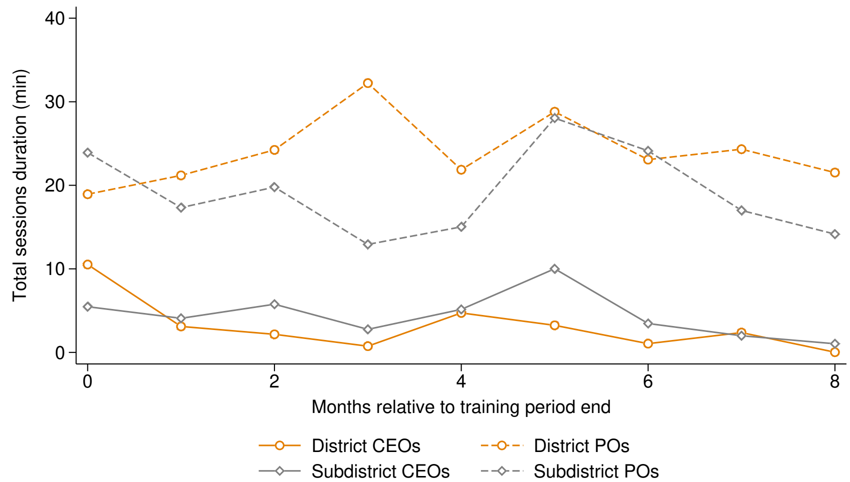

(b) Implementation Challenges - Subdistrict Reported




(c) Performance Metrics - District Reported

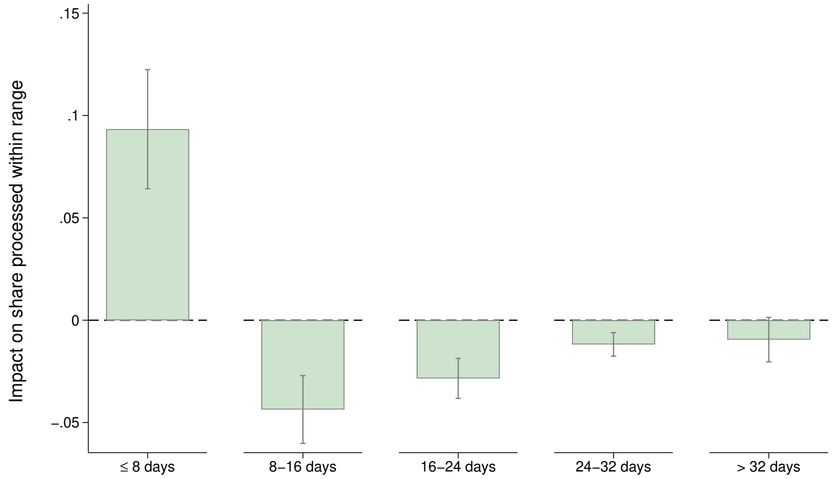

Notes: Panel A shows MGNREGS issues ordered by average rank in terms of importance to rural household MGNREGS participants, based on baseline reports by subdistrict POs and CEOs. Panel B shows MGNREGS challenges faced by subdistrict officers ordered by average rank of importance, based on baseline reports by subdistrict POs and CEOs. Panel C of the figure shows dimensions of MGNREGS implementation ordered by average rank in terms of importance for assessment of subdistrict MGNREGS performance by district supervisors, based on baseline reports by District POs. Circles plot the mean and boxes show the median and interquartile range. Appendix Table C.4 provides detailed definitions for the categories in each panel.

Figure 2: Bureaucrat PayDash Usage Over Time




Notes: The figure shows monthly average PayDash usage duration for each of the four bureaucrat groups (district and subdistrict CEOs and POs) over the maximum range available for both states, following the two-month period during which group and individual-follow-up PayDash training sessions occurred and excluding Madhya Pradesh outage-month observations.

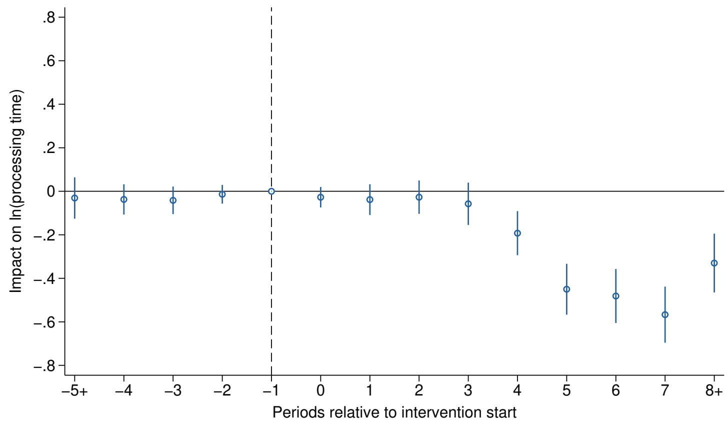
Figure 3: Effects on Processing Time Distribution



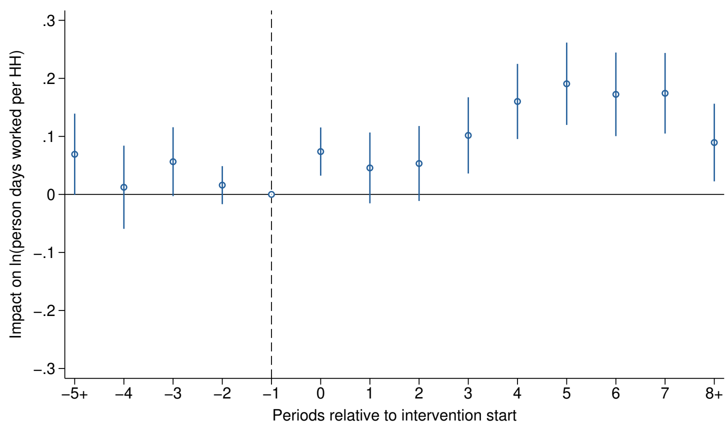

Notes: The figure shows estimates following Equation (1) for the impacts of PayDash provision on the share of attendance registers processed within the time range specified in each column. Standard errors in the underlying subdistrict-month-level regressions are clustered at the district level, and error bars in the figure depict 95% confidence intervals.

Figure 4: Dynamics of PayDash Impacts

(a) Log processing time



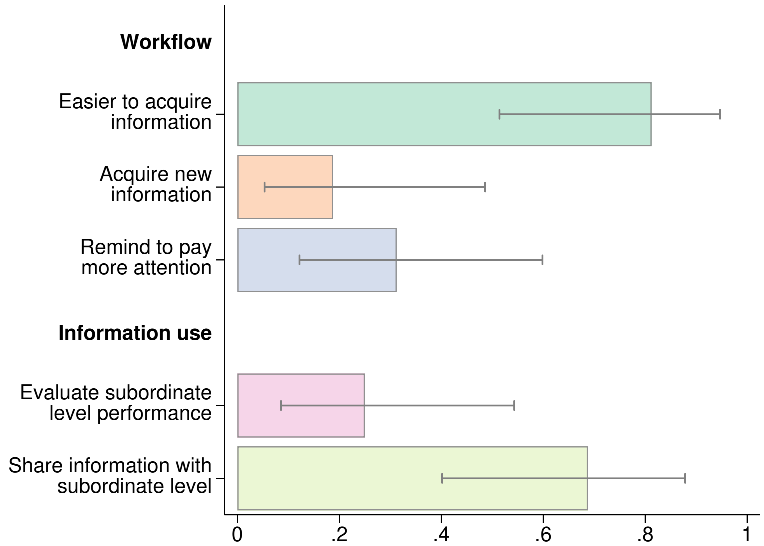

(b) Log days per working household



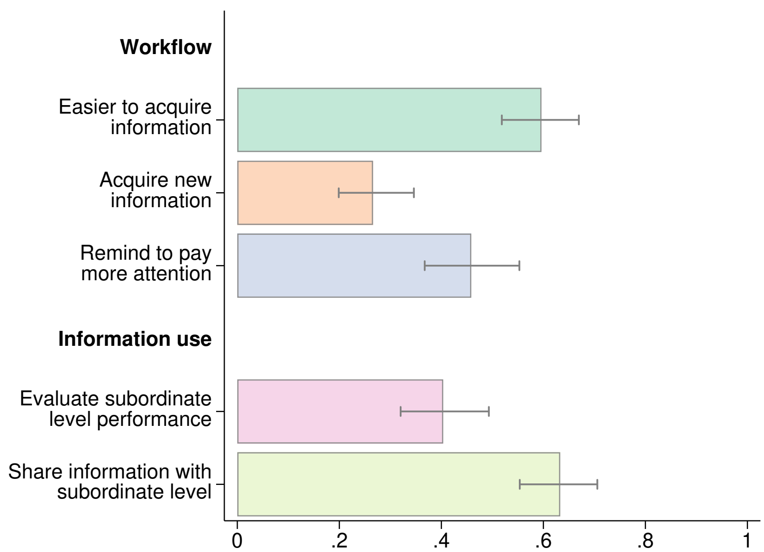

Notes: The figure shows estimates following Equation (2) for the impacts PayDash provision on log average processing time (Panel A) and log days worked per participating household (Panel B). Standard errors in the underlying subdistrict-month-level regressions are clustered at the district level, and error bars in the figure depict 95% confidence intervals.

Figure 5: Mechanisms of Impact - Bureaucrat Self-Reports

(a) District Supervisors




(b) Subdistrict Officers




Notes: The figure presents the share of treated respondents in Madhya Pradesh at the district (Panel A) and subdistrict (Panel B) PO levels agreeing in the follow-up survey with different statements. Bars in the figure depict 95% confidence intervals. Within each panel, “Workflow” presents the share indicating each of the following was true about their use of platform: “PayDash made it easier to acquire information about wage payment processing in my [sub]district”, “PayDash allowed me to acquire information I didn’t have before about wage payment processing in my [sub]district”, and “PayDash reminded me to pay more attention to wage payment processing in my [sub]district”. “Information use” presents the share indicating they used PayDash in each of the following ways: “To evaluate the performance of subordinate officers who work on MGNREGS at the [subdistrict/GP] level”, and “To share relevant information with subordinate officers who work on MGNREGS at the [subdistrict/GP] level”.

Table 1: Bureaucrat Monthly PayDash Usage

| | Sessions | | Duration (min) | | Calls and messages | |
|---|---|---|---|---|---|---|
| | POs | CEOs | POs | CEOs | POs | CEOs |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: 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] |
| Both levels 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 |
| *Panel B: District Supervisors* | | | | | | |
| 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] |
| Both levels 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 |

Notes: The first row in each panel reports means and standard deviations of each column's listed officer PayDash usage variable, calculated at the subdistrict-month (Panel A) or district-month (Panel B) level and restricted to treatment months in localities receiving PayDash only at the corresponding administrative level. Odd (even) columns consider usage by program (chief executive) officers. The second row of each panel shows the coefficient and standard error for an indicator for PayDash provision at both administrative levels from a regression of each column's listed usage variable on that indicator as well as month and strata fixed effects, restricted to treatment months in localities receiving PayDash at the corresponding administrative level. Standard errors clustered at the district level in parentheses. "Sessions" includes both web and mobile usage, and "Duration" captures mobile usage only. Significant at *10 percent, **5 percent,***1 percent.

Table 2: Usage Impacts of Exogenous Shock to Real-time Data Availability

| | Sessions | | Duration (min) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Subdistrict Officers* | | | | |
| Outage month | -2.84*** | | -17.60*** | |
| | (0.62) | | (3.90) | |
| Pre-outage month | | 2.93*** | | 16.36*** |
| | | (0.69) | | (5.06) |
| Post-outage month | | 2.75*** | | 18.84*** |
| | | (0.77) | | (4.47) |
| Coeff. equality, p-value | | 0.818 | | 0.656 |
| Non-outage mean | 5.03 | 5.03 | 24.51 | 24.51 |
| Observations | 1,016 | 1,016 | 1,016 | 1,016 |
| *Panel B: District Supervisors* | | | | |
| Outage month | -2.44** | | -8.71** | |
| | (0.91) | | (4.16) | |
| Pre-outage month | | 3.22** | | 10.90* |
| | | (1.53) | | (5.76) |
| Post-outage month | | 1.66 | | 6.52 |
| | | (1.15) | | (4.48) |
| Coeff. equality, p-value | | 0.446 | | 0.480 |
| Non-outage mean | 4.58 | 4.58 | 15.13 | 15.13 |
| Observations | 160 | 160 | 160 | 160 |

Notes: Columns in each panel report estimates from locality-month-level regressions of the listed variable on an indicator for the PayDash data outage month (odd columns) or indicators for pre- and post-outage months (even columns). Also included in the regressions are subdistrict (Panel A) or district (Panel B) fixed effects. The sample in each regression is restricted to observations in Madhya Pradesh within three months of the data outage in localities receiving PayDash at the listed officer level. All usage measures are calculated as the sum of CEO and PO usage within a given level. "Sessions" includes both web and mobile usage, while "Duration" captures mobile usage only. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 3: PayDash Impacts on MGNREGS Outcomes

| | Payment processing | | | | Program scale | | | |
|---|---|---|---|---|---|---|---|---|
| | Log processing time | Share processed "late" (>8 days) | Absolute deviation (days) | Share of payment requests rejected | Log days per working household | Log working households | Log days worked | Log active worksites |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Panel A: Pooled Treatment* | | | | | | | | |
| Any PayDash | -0.181*** | -0.093*** | -0.633*** | -0.010*** | 0.096*** | -0.012 | 0.084 | 0.210*** |
| | (0.035) | (0.015) | (0.222) | (0.003) | (0.018) | (0.062) | (0.064) | (0.063) |
| Control mean | 2.12 | 0.397 | 4.95 | 0.049 | 2.41 | 7.46 | 9.87 | 6.07 |
| Observations | 13,443 | 13,443 | 13,443 | 13,177 | 13,443 | 13,443 | 13,443 | 11,693 |
| *Panel B: Impact Seasonality* | | | | | | | | |
| High season | | | | | | | | |
| × Any PayDash | 0.062* | 0.023* | 0.276 | -0.005 | 0.020 | 0.068* | 0.088** | 0.169*** |
| | (0.033) | (0.013) | (0.158) | (0.005) | (0.017) | (0.038) | (0.041) | (0.047) |
| Any PayDash | -0.204*** | -0.101*** | -0.731*** | -0.008** | 0.087*** | -0.041 | 0.047 | 0.148** |
| | (0.039) | (0.016) | (0.239) | (0.004) | (0.018) | (0.059) | (0.061) | (0.060) |
| Any + High×Any, p-value | 0.000 | 0.000 | 0.053 | 0.003 | 0.000 | 0.711 | 0.079 | 0.000 |
| Observations | 13,443 | 13,443 | 13,443 | 13,177 | 13,443 | 13,443 | 13,443 | 11,693 |

Notes: In Panel A, columns report estimates following Equation (1). The analysis in Panel B additionally includes a high season indicator (not shown) and its interaction with the pooled treatment indicator. Panel B also presents the p-value for the total MGNREGS high season impact of Any PayDash. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 4: Effects of PayDash – Treatment Arms

| | Payment processing | | | | Program scale | | | |
|---|---|---|---|---|---|---|---|---|
| | Log processing time | Share processed "late" (>8 days) | Absolute deviation (days) | Share of payment requests rejected | Log days per working household | Log working households | Log days worked | Log active worksites |
| | (1) | (2) | (3 | (4) | (5) | (6) | (7) | (8) |
| *Panel A: Treatment Arms* | | | | | | | | |
| District Only PayDash | -0.184*** | -0.090*** | -0.777** | -0.005 | 0.131*** | 0.063 | 0.194 | 0.275*** |
| | (0.059) | (0.025) | (0.376) | (0.006) | (0.025) | (0.100) | (0.118) | (0.099) |
| Subdistrict Only PayDash | -0.182*** | -0.098*** | -0.661** | -0.002 | 0.112*** | -0.057 | 0.055 | 0.175* |
| | (0.050) | (0.020) | (0.321) | (0.007) | (0.026) | (0.059) | (0.064) | (0.098) |
| Combination PayDash | -0.178*** | -0.093*** | -0.495 | -0.018*** | 0.057** | -0.042 | 0.015 | 0.186** |
| | (0.052) | (0.022) | (0.327) | (0.004) | (0.025) | (0.087) | (0.078) | (0.072) |
| D + S = C, p-value | 0.029 | 0.010 | 0.078 | 0.280 | 0.000 | 0.699 | 0.099 | 0.070 |
| D = S = C, p-value | 0.996 | 0.957 | 0.815 | 0.067 | 0.068 | 0.509 | 0.364 | 0.640 |
| Observations | 13,443 | 13,443 | 13,443 | 13,177 | 13,443 | 13,443 | 13,443 | 11,693 |
| *Panel B: Impact Seasonality* | | | | | | | | |
| High season | | | | | | | | |
| × District Only PayDash | 0.096*** | 0.036*** | 0.415** | -0.007 | -0.006 | 0.084* | 0.078 | 0.206*** |
| | (0.033) | (0.013) | (0.188) | (0.006) | (0.021) | (0.050) | (0.054) | (0.066) |
| × Subdistrict Only PayDash | 0.088* | 0.038* | 0.319 | -0.012* | 0.003 | -0.004 | -0.000 | 0.097* |
| | (0.051) | (0.020) | (0.243) | (0.007) | (0.023) | (0.049) | (0.052) | (0.056) |
| × Combination PayDash | 0.009 | -0.001 | 0.110 | 0.002 | 0.058** | 0.109** | 0.167*** | 0.191*** |
| | (0.050) | (0.018) | (0.243) | (0.006) | (0.024) | (0.053) | (0.050) | (0.056) |
| District Only PayDash | -0.217*** | -0.102*** | -0.920** | -0.003 | 0.129*** | 0.034 | 0.163 | 0.210** |
| | (0.063) | (0.026) | (0.396) | (0.006) | (0.024) | (0.093) | (0.107) | (0.097) |
| Subdistrict Only PayDash | -0.215*** | -0.112*** | -0.788** | 0.001 | 0.107*** | -0.068 | 0.040 | 0.127 |
| | (0.056) | (0.022) | (0.333) | (0.008) | (0.028) | (0.058) | (0.061) | (0.094) |
| Combination PayDash | -0.183*** | -0.093*** | -0.531 | -0.017*** | 0.038 | -0.082 | -0.044 | 0.119* |
| | (0.054) | (0.022) | (0.346) | (0.004) | (0.024) | (0.081) | (0.075) | (0.070) |
| Observations | 13,443 | 13,443 | 13,443 | 13,177 | 13,443 | 13,443 | 13,443 | 11,693 |

Notes: Columns in Panel A report estimates following Equation (3) and also present p-values from tests of the equality of impacts across treatment arms ("D = S = C") and of the sum of the District Only and Subdistrict Only PayDash impacts with the Combination PayDash impact ("D + S = C"). Columns in Panel B report estimates from analysis additionally including an MGNREGS high season indicator (not shown) and its interactions with the treatment-arm-specific treatment indicators. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 5: Heterogeneity by Administrative Structure

| | Payment processing | | | | Program scale | | | |
|---|---|---|---|---|---|---|---|---|
| | Log processing time | Share processed "late" (>8 days) | Absolute deviation (days) | Share of payment requests rejected | Log days per working household | Log working households | Log days worked | Log active worksites |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| High GPs per subdistrict × Any PayDash | -0.119** | -0.062*** | -0.495 | 0.003 | -0.000 | -0.086 | -0.086 | -0.007 |
| | (0.056) | (0.023) | (0.368) | (0.007) | (0.029) | (0.086) | (0.094) | (0.091) |
| Any PayDash | -0.132*** | -0.068*** | -0.429 | -0.011** | 0.096*** | 0.024 | 0.120 | 0.213*** |
| | (0.044) | (0.017) | (0.300) | (0.005) | (0.022) | (0.077) | (0.081) | (0.074) |
| Any + High×Any, p-value | 0.000 | 0.000 | 0.001 | 0.048 | 0.000 | 0.381 | 0.651 | 0.014 |
| Control outcome mean, high | 2.11 | 0.387 | 6.99 | 0.051 | 2.50 | 7.58 | 10.08 | 6.22 |
| Control outcome mean, low | 2.14 | 0.406 | 6.10 | 0.048 | 2.33 | 7.36 | 9.69 | 5.94 |
| Observations | 13,443 | 13,443 | 13,443 | 13,177 | 13,443 | 13,443 | 13,443 | 11,693 |

Notes: Columns report estimates following Equation (1) additionally including an interaction of the treatment indicator with an indicator for being an above-state-median district in terms of average number of panchayats per subdistrict ("High GPs-per-subdistrict"). Columns also present the p-value for the total MGNREGS impact of Any PayDash in high-GPs-per-subdistrict areas and control means by "high" and "low", corresponding respectively to above- and below-state-median districts in terms of average number of panchayats per subdistrict. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 6: Impacts on Bureaucrat and Citizen Outcomes

| | Subdistrict officers | | Social audits | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | Officer-related issue | | |
| | Posting transfer | Knowledge gap | Community work demand | Issue irregularity index | GP level | Subdistrict level | District level |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Panel A: Pooled Treatment* | | | | | | | |
| Any PayDash | -0.057 | -0.078* | 0.124** | -0.029 | -0.018 | 0.003 | -0.000 |
| | (0.044) | (0.042) | (0.061) | (0.056) | (0.028) | (0.009) | (0.000) |
| Control mean | 0.447 | 0.418 | 0.297 | 0.000 | 0.126 | 0.018 | 0.000 |
| Observations | 1,122 | 176 | 20,621 | 20,621 | 20,621 | 20,621 | 20,621 |
| *Panel B: Treatment Arms* | | | | | | | |
| District Only PayDash | -0.106** | -0.067 | 0.088 | 0.004 | 0.005 | 0.011 | -0.000 |
| | (0.051) | (0.056) | (0.076) | (0.070) | (0.035) | (0.012) | (0.000) |
| Subdistrict Only PayDash | 0.029 | -0.100** | 0.102 | -0.030 | -0.032 | -0.010 | -0.000 |
| | (0.055) | (0.048) | (0.076) | (0.056) | (0.028) | (0.010) | (0.000) |
| Combination PayDash | -0.073 | -0.072 | 0.183** | -0.063 | -0.026 | 0.009 | -0.000 |
| | (0.051) | (0.048) | (0.074) | (0.056) | (0.030) | (0.012) | (0.000) |
| D + S = C, p-value | 0.955 | 0.192 | 0.944 | 0.621 | 0.994 | 0.629 | 0.200 |
| D = S = C, p-value | 0.036 | 0.780 | 0.435 | 0.289 | 0.351 | 0.115 | 0.520 |
| Observations | 1,122 | 176 | 20,621 | 20,621 | 20,621 | 20,621 | 20,621 |

Notes: In Panel A, column (1) reports estimates from regressions at the subdistrict-position level of the listed variable on a pooled treatment indicator as well as strata fixed effects and a PO indicator. Column (2) reports estimates from regressions at the subdistrict PO level of the listed variable on a pooled treatment indicator and strata fixed effects. Columns (3) through (7) report estimates from regressions at the audit level of the listed variable on a pooled treatment indicator and strata fixed effects. For each column, Panel B repeats the analysis in Panel A, replacing the pooled treatment indicator with treatment-arm-specific indicators and also presenting p-values from tests of the equality of impacts across treatment arms ("D = S = C") and of the sum of the District Only and Subdistrict Only PayDash impacts with the Combination PayDash impact ("D + S = C"). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 7: Benefit-Cost Analysis

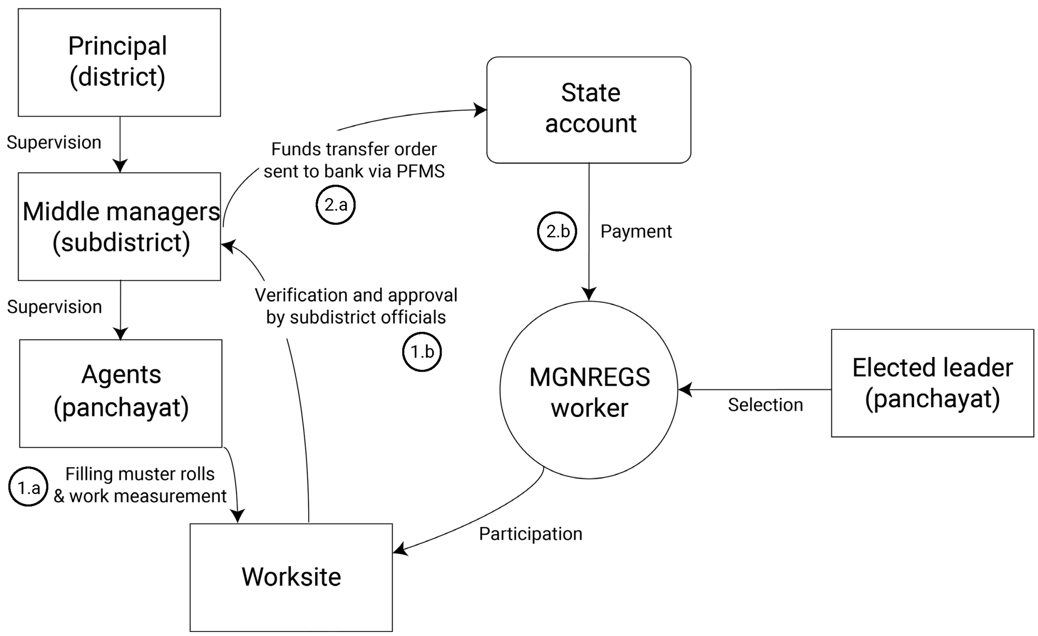
| Category | Amount | Units | Source |
|---|---|---|---|
| *Panel A: Benefits* | | | |
| Time to payment-related | | | |
| Reduced time to payment | -1.30 | Days per workspell | Table 3; 0.94 pass-through rate from processing time to final payment applied. |
| Loans affected | 3,278 | Loans per subdistrict-month | Tables 3 and A7; Working HHs per subdistrict-month * workspells per HH. |
| Loan principal reduction | $2.12 | $ per loan | PLFS 2017-18 and RBI 2012, 2017 data; One-day household consumption cost based on state-wise average rural household sizes and poverty thresholds. |
| Loan interest reduction | $0.06 | $ per loan | AIDIS 2019 data; Interest rate based on loans taken in 2017-18 from moneylenders by study state households in bottom two expenditure quintiles. |
| Total interest cost averted | $203 | $ per subdistrict-month | Authors' calculations. |
| Workfare access-related | | | |
| Additional person-days worked | 1,695 | Days per subdistrict-month | Table 3. |
| Total additional workday wages | $4,433 | $ per subdistrict-month | Official 2017-18 state-specific daily wage rates applied. |
| *Panel B: Costs* | | | |
| PayDash | | | |
| Initial development | $98,420 | $ | Actual costs. |
| Initial roll-out | $37,139 | $ | Actual costs. |
| Annual development maintenance | $25,074 | $ per year | Actual costs. |
| Annual development oversight | $10,584 | $ per year | Actual costs. |
| Annual transfer tracking and re-training | $15,526 | $ per year | Actual costs; Authors' calculations. |
| Comparison: Adding subdistrict bureaucrats | | | |
| Additional bureaucrats hired | 5.33 | Officers per subdistrict | Authors' calculations. |
| Bureaucrat wages and reimbursements | $399 | $ per officer-month | Baseline survey data. |
| *Panel C: Scaled Estimates* | | | |
| Annual benefits: Time to payment-related | $1,409,954 | $ per year | Panel A; Authors' calculations. |
| Annual benefits: Workfare access-related | $30,747,336 | $ per year | Panel A; Authors' calculations. |
| Initial year costs: PayDash | $186,742 | $ per year | Panel B; Authors' calculations. |
| Future year costs: PayDash | $51,184 | $ per year | Panel B; Authors' calculations. |
| Annual costs: Adding subdistrict bureaucrats | $14,729,343 | $ per year | Panel B; Authors' calculations. |
| *Panel D: Benefit-Cost Ratio* | | | |
| Initial year: PayDash | 172:1 | | Panel C; Authors' calculations. |
| Future years: PayDash | 628:1 | | Panel C; Authors' calculations. |
| Annual: Adding bureaucrats | 2:1 | | Panel C; Authors' calculations. |

Notes: AIDIS is the All India Debt and Investment Survey, PLFS is the Periodic Labour Force Survey, and RBI is the Reserve Bank of India. Jharkhand and Madhya Pradesh contain 578 subdistricts in total. Appendix C.5 provides additional details.

# Online Appendix

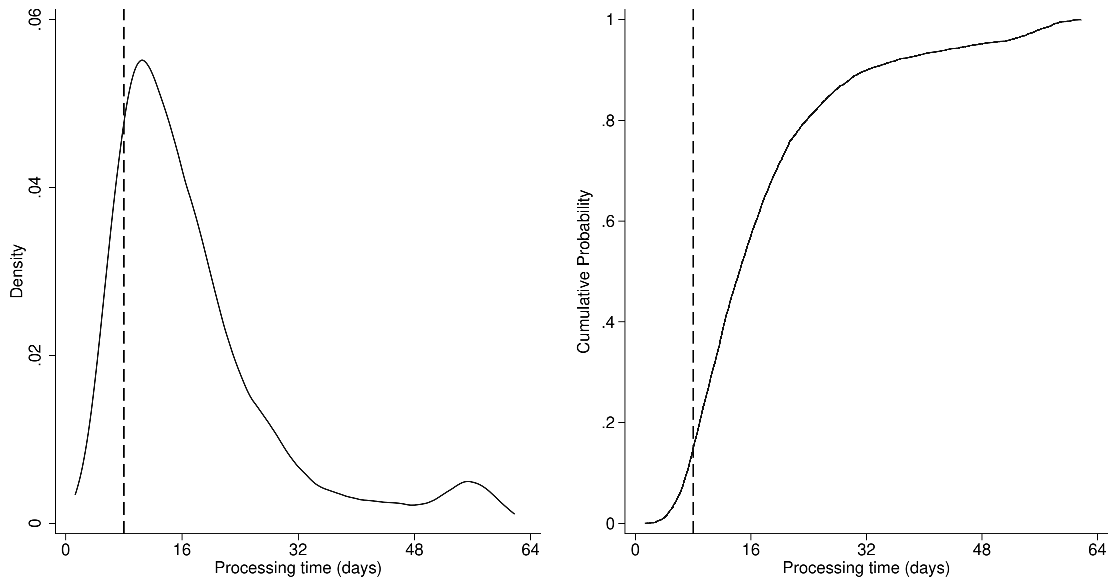
# Appendix A: Additional Figures and Tables

Figure A1: MGNREGS Work, Verification, and Payment Process



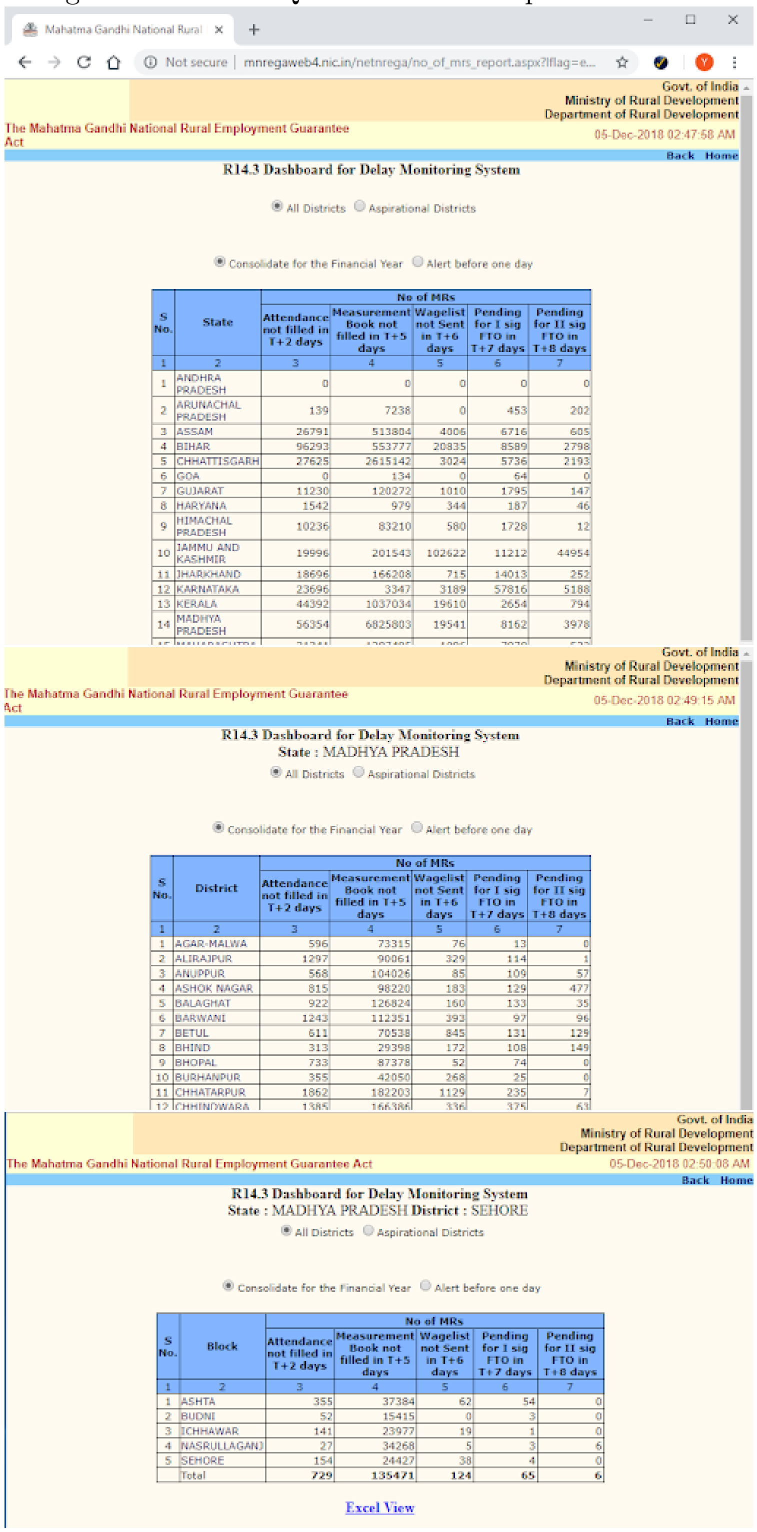

Notes: The figure shows a stylized representation of MGNREGS participation, work verification, and payment processing.

Figure A2: Attendance Register Processing Times - Year Prior to Intervention




Notes: The figure plots the kernel density estimate and empirical cumulative distribution function of subdistrict-month-level average payment processing time for the February 2016 to January 2017 range. Density estimated using an Epanechnikov kernel. Plots exclude observations with values above the 99.5th percentile. The dashed vertical line corresponds to the government's mandated eight-day maximum processing time.

Figure A3: Status Quo Website Example Screenshots



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**R14.3 Dashboard for Delay Monitoring System**

All Districts  Aspirational Districts

Consolidate for the Financial Year  Alert before one day

| S No. | State | No of MRs: Attendance not filled in T+2 days | Measurement Book not filled in T+5 days | Wagelist not Sent in T+6 days | Pending for I sig FTO in T+7 days | Pending for II sig FTO in T+8 days |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | ANDHRA PRADESH | 0 | 0 | 0 | 0 | 0 |
| 2 | ARUNACHAL PRADESH | 139 | 7238 | 0 | 453 | 202 |
| 3 | ASSAM | 26791 | 513804 | 4006 | 6716 | 605 |
| 4 | BIHAR | 96293 | 553777 | 20835 | 8589 | 2798 |
| 5 | CHHATTISGARH | 27625 | 2615142 | 3024 | 5736 | 2193 |
| 6 | GOA | 0 | 134 | 0 | 64 | 0 |
| 7 | GUJARAT | 11230 | 120272 | 1010 | 1795 | 147 |
| 8 | HARYANA | 1542 | 979 | 344 | 187 | 46 |
| 9 | HIMACHAL PRADESH | 10236 | 83210 | 580 | 1728 | 12 |
| 10 | JAMMU AND KASHMIR | 19996 | 201543 | 102622 | 11212 | 44954 |
| 11 | JHARKHAND | 18696 | 166208 | 715 | 14013 | 252 |
| 12 | KARNATAKA | 23696 | 3347 | 3189 | 57816 | 5188 |
| 13 | KERALA | 44392 | 1037034 | 19610 | 2654 | 794 |
| 14 | MADHYA PRADESH | 56354 | 6825803 | 19541 | 8162 | 3978 |

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**R14.3 Dashboard for Delay Monitoring System**
State : MADHYA PRADESH

All Districts  Aspirational Districts

Consolidate for the Financial Year  Alert before one day

| S No. | District | No of MRs: Attendance not filled in T+2 days | Measurement Book not filled in T+5 days | Wagelist not Sent in T+6 days | Pending for I sig FTO in T+7 days | Pending for II sig FTO in T+8 days |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | AGAR-MALWA | 596 | 73315 | 76 | 13 | 0 |
| 2 | ALIRAJPUR | 1297 | 90061 | 329 | 114 | 1 |
| 3 | ANUPPUR | 568 | 104026 | 85 | 109 | 57 |
| 4 | ASHOK NAGAR | 815 | 98220 | 183 | 129 | 477 |
| 5 | BALAGHAT | 922 | 126824 | 160 | 133 | 35 |
| 6 | BARWANI | 1243 | 112351 | 393 | 97 | 96 |
| 7 | BETUL | 611 | 70538 | 845 | 131 | 129 |
| 8 | BHIND | 313 | 29398 | 172 | 108 | 149 |
| 9 | BHOPAL | 733 | 87378 | 52 | 74 | 0 |
| 10 | BURHANPUR | 355 | 42050 | 268 | 25 | 0 |
| 11 | CHHATARPUR | 1862 | 182203 | 1129 | 235 | 7 |
| 12 | CHHINDWARA | 1385 | 166386 | 336 | 375 | 63 |

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**R14.3 Dashboard for Delay Monitoring System**
State : MADHYA PRADESH District : SEHORE

All Districts  Aspirational Districts

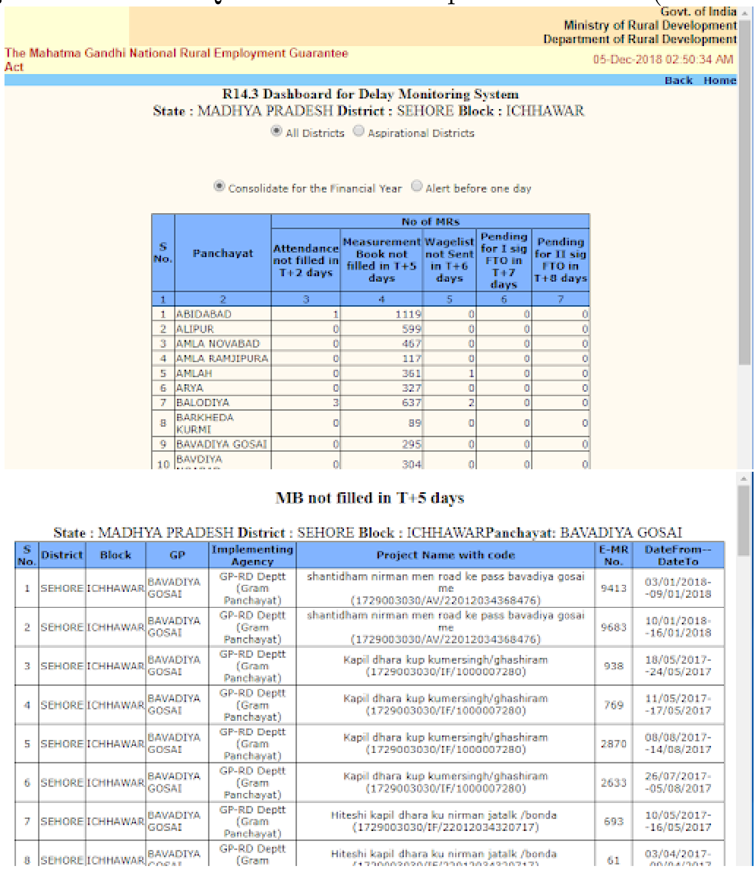
Consolidate for the Financial Year  Alert before one day

| S No. | Block | No of MRs: Attendance not filled in T+2 days | Measurement Book not filled in T+5 days | Wagelist not Sent in T+6 days | Pending for I sig FTO in T+7 days | Pending for II sig FTO in T+8 days |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | ASHTA | 355 | 37384 | 62 | 54 | 0 |
| 2 | BUDNI | 52 | 15415 | 0 | 3 | 0 |
| 3 | ICHHAWAR | 141 | 23977 | 19 | 1 | 0 |
| 4 | NASRULLAGANJ | 27 | 34268 | 5 | 3 | 6 |
| 5 | SEHORE | 154 | 24427 | 38 | 4 | 0 |
|  | Total | 729 | 135471 | 124 | 65 | 6 |

Excel View

Notes: The figure shows example screenshots at the state (top), district (middle), and subdistrict (bottom) list levels from the MGRNEGS "R14.3 Dashboard for Delay Monitoring System", https://mnregaweb4.nic.in/netnrega/no_of_mrs_report.aspx, as accessed on December 5, 2018.

Figure A3: Status Quo Website Example Screenshots (continued)



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**R14.3 Dashboard for Delay Monitoring System**

**State :** MADHYA PRADESH **District :** SEHORE **Block :** ICHHAWAR

All Districts Aspirational Districts

Consolidate for the Financial Year Alert before one day

| S No. | Panchayat | No of MRs | | | | |
|---|---|---|---|---|---|---|
| | | Attendance not filled in T+2 days | Measurement Book not filled in T+5 days | Wagelist not Sent in T+6 days | Pending for I sig FTO in T+7 days | Pending for II sig FTO in T+8 days |
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | ABIDABAD | 1 | 1119 | 0 | 0 | 0 |
| 2 | ALIPUR | 0 | 599 | 0 | 0 | 0 |
| 3 | AMLA NOVABAD | 0 | 467 | 0 | 0 | 0 |
| 4 | AMLA RAMJIPURA | 0 | 117 | 0 | 0 | 0 |
| 5 | AMLAH | 0 | 361 | 1 | 0 | 0 |
| 6 | ARYA | 0 | 327 | 0 | 0 | 0 |
| 7 | BALODIYA | 3 | 637 | 2 | 0 | 0 |
| 8 | BARKHEDA KURMI | 0 | 89 | 0 | 0 | 0 |
| 9 | BAVADIYA GOSAI | 0 | 295 | 0 | 0 | 0 |
| 10 | BAVDIYA | 0 | 304 | 0 | 0 | 0 |

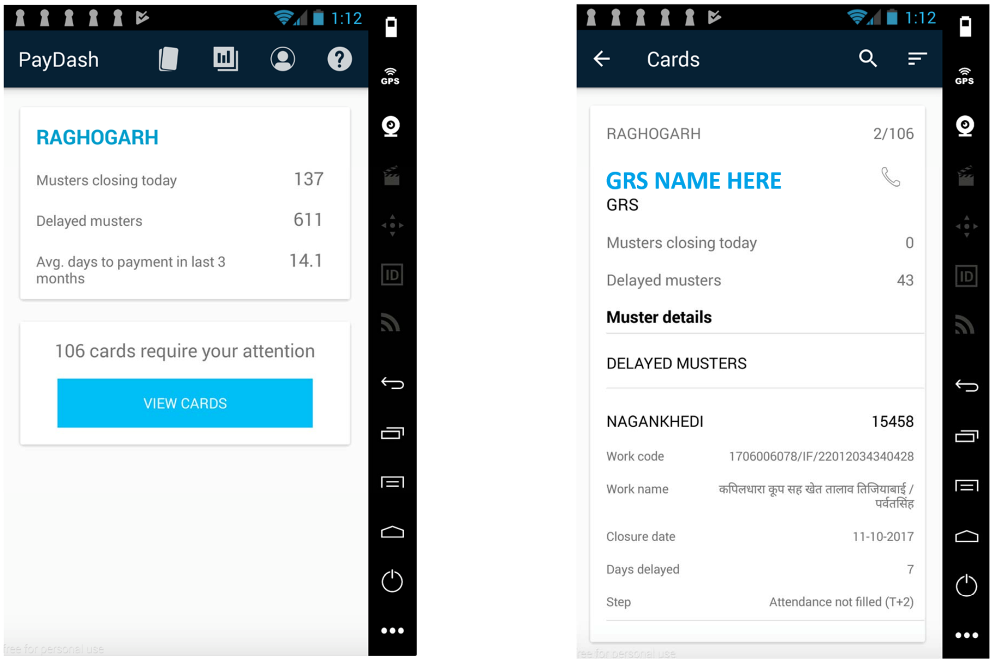
**MB not filled in T+5 days**

**State :** MADHYA PRADESH **District :** SEHORE **Block :** ICHHAWAR**Panchayat:** BAVADIYA GOSAI

| S No. | District | Block | GP | Implementing Agency | Project Name with code | E-MR No. | DateFrom--DateTo |
|---|---|---|---|---|---|---|---|
| 1 | SEHORE | ICHHAWAR | BAVADIYA GOSAI | GP-RD Deptt (Gram Panchayat) | shantidham nirman men road ke pass bavadiya gosai me (1729003030/AV/22012034368476) | 9413 | 03/01/2018--09/01/2018 |
| 2 | SEHORE | ICHHAWAR | BAVADIYA GOSAI | GP-RD Deptt (Gram Panchayat) | shantidham nirman men road ke pass bavadiya gosai me (1729003030/AV/22012034368476) | 9683 | 10/01/2018--16/01/2018 |
| 3 | SEHORE | ICHHAWAR | BAVADIYA GOSAI | GP-RD Deptt (Gram Panchayat) | Kapil dhara kup kumersingh/ghashiram (1729003030/IF/1000007280) | 938 | 18/05/2017--24/05/2017 |
| 4 | SEHORE | ICHHAWAR | BAVADIYA GOSAI | GP-RD Deptt (Gram Panchayat) | Kapil dhara kup kumersingh/ghashiram (1729003030/IF/1000007280) | 769 | 11/05/2017--17/05/2017 |
| 5 | SEHORE | ICHHAWAR | BAVADIYA GOSAI | GP-RD Deptt (Gram Panchayat) | Kapil dhara kup kumersingh/ghashiram (1729003030/IF/1000007280) | 2870 | 08/08/2017--14/08/2017 |
| 6 | SEHORE | ICHHAWAR | BAVADIYA GOSAI | GP-RD Deptt (Gram Panchayat) | Kapil dhara kup kumersingh/ghashiram (1729003030/IF/1000007280) | 2633 | 26/07/2017--05/08/2017 |
| 7 | SEHORE | ICHHAWAR | BAVADIYA GOSAI | GP-RD Deptt (Gram Panchayat) | Hiteshi kapil dhara ku nirman jatalk /bonda (1729003030/IF/22012034320717) | 693 | 10/05/2017--16/05/2017 |
| 8 | SEHORE | ICHHAWAR | BAVADIYA | GP-RD Deptt (Gram | Hiteshi kapil dhara ku nirman jatalk /bonda | 61 | 03/04/2017- |

Notes: The figure shows a example screenshots at the GP (top) and attendance register (bottom) list levels from the MGRNEGS "R14.3 Dashboard for Delay Monitoring System", https://mnregaweb4.nic.in/netnrega/no_of_mrs_report.aspx, as accessed on December 5, 2018.

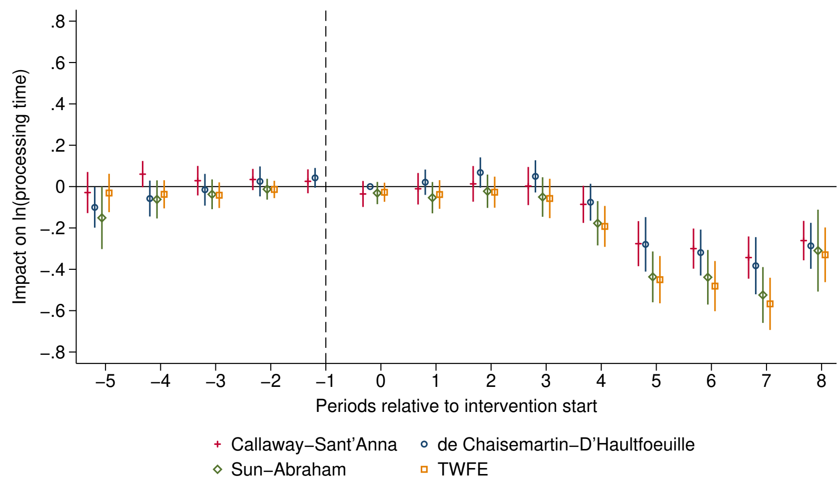
Figure A4: Subdistrict PayDash Example Screenshots



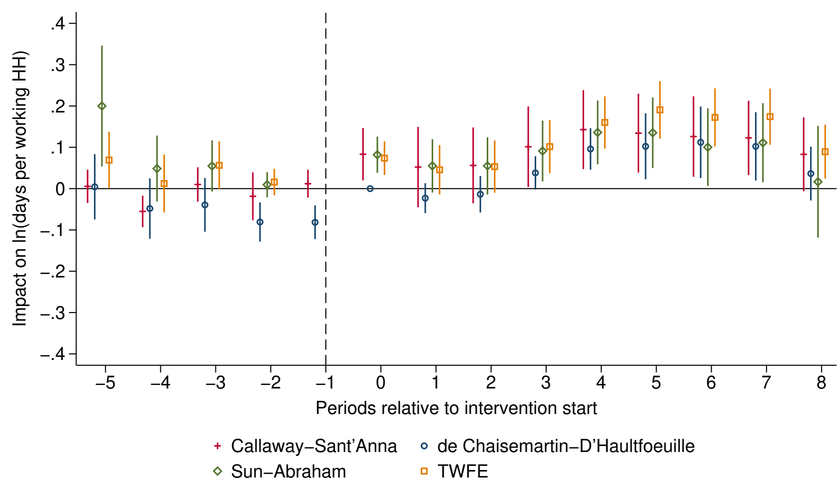

Notes: The figure shows an example subdistrict-level PayDash mobile application homescreen (left), providing a daily-updated overview of payment processing within a subdistrict officer's jurisdiction; and a "card" screen (right) with GP-by-subordinate-level information on pending delayed documents for which that officer is responsible and an icon that can be clicked to directly contact that officer.

Figure A5: Dynamics of PayDash Impacts - Alternative Estimators

(a) Log processing time



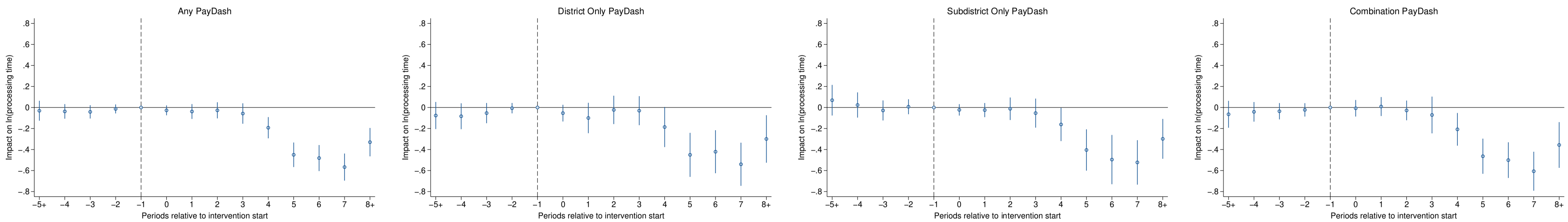

(b) Log days per working household



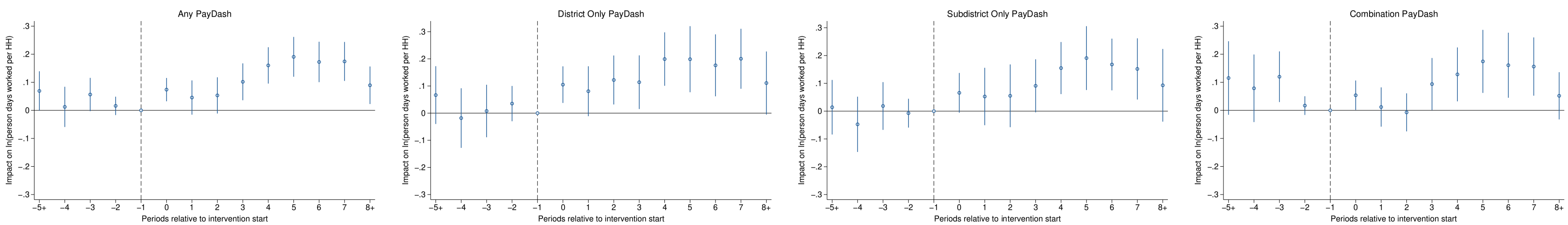

Notes: The figure shows event study plots for the impacts of PayDash, constructed based on Equation (2) and the corresponding Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfoeuille (2024), and Sun and Abraham (2021) estimators. The Sun and Abraham-based analysis also includes district trend controls, which is possible for that alternative estimator. Standard errors in the underlying analyses are clustered at the district level, and error bars in the figure depict 95% confidence intervals.

Figure A6: Dynamics of PayDash Impacts - Treatment Arms

(a) Log processing time

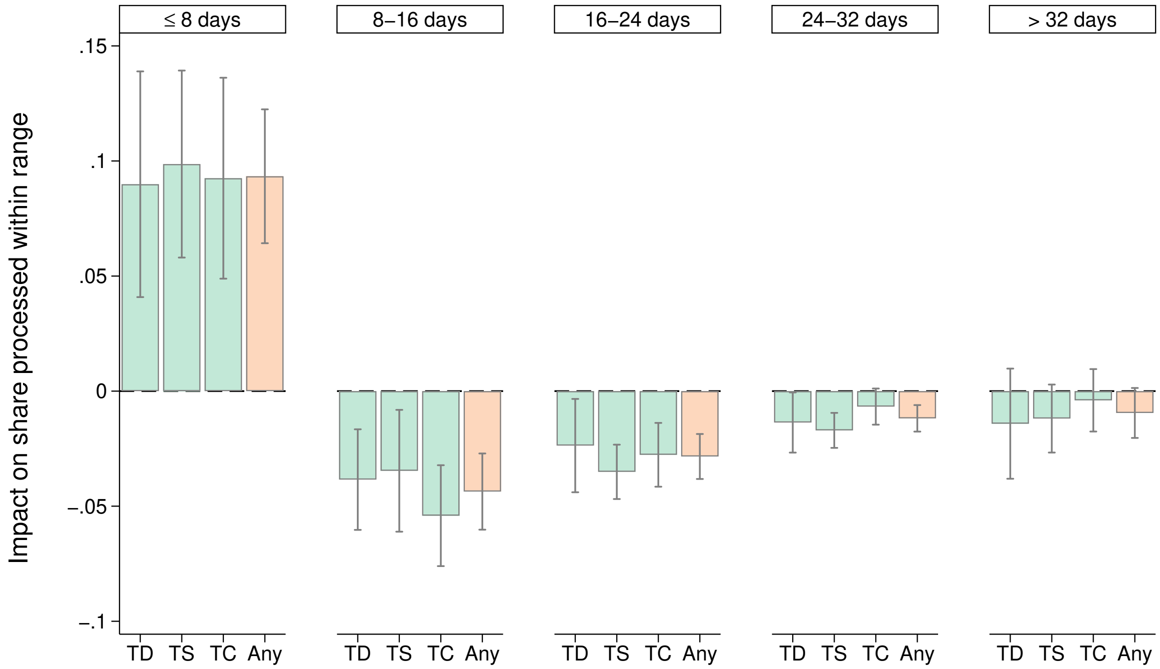



(b) Log days per working household




Notes: The figure shows event-study plots, constructed based on Equation (2) for the impacts of any PayDash provision and separately by PayDash treatment arm, with outcomes of log average processing time (Panel A) and log days per working household (Panel B). Standard errors in the underlying subdistrict-month-level regressions are clustered at the district level, and error bars in the figure depict 95% confidence intervals.

Figure A7: Impacts of PayDash on Processing Time Distribution - Treatment Arms




Notes: The figure shows estimates following Equation (1) for the impacts of District Only PayDash ("TD"), Subdistrict Only PayDash ("TS"), and Combination PayDash ("TC"), with outcomes of the share of attendance registers processed within the time range specified in each column header. The figure also shows estimates for the impacts of any PayDash provision ("Any"). Standard errors in the underlying subdistrict-month-level regressions are clustered at the district level, and error bars in the figure depict 95% confidence intervals.

Table A1: Baseline Characteristics

| | Overall Mean (1) | District Only (2) | Subdistrict Only (3) | Combination (4) | Joint p-value (5) | Obs (6) |
|---|---|---|---|---|---|---|
| *Panel A: Administrative Characteristics* | | | | | | |
| Subdistricts per district | 7.70 | 1.18 | -0.43 | 0.38 | 0.429 | 73 |
| | [3.99] | (1.11) | (0.76) | (1.13) | | |
| Total population (x1,000) | 1420.60 | -202.18 | -144.76 | -43.94 | 0.825 | 73 |
| | [621.90] | (254.79) | (215.81) | (226.83) | | |
| Rural population share | 77.26 | 2.91 | 0.24 | -3.14 | 0.602 | 73 |
| | [15.88] | (4.81) | (5.56) | (5.25) | | |
| GPs per subdistrict | 47.09 | -1.53 | 5.16* | -0.02 | 0.214 | 561 |
| | [32.12] | (3.31) | (3.01) | (2.34) | | |
| Processing time (days) | 17.69 | -0.90 | 1.19 | -0.84 | 0.178 | 561 |
| | [7.49] | (1.36) | (1.14) | (1.13) | | |
| Absolute deviation (days) | 9.45 | -0.55 | 0.73 | -0.44 | 0.207 | 561 |
| | [3.98] | (0.65) | (0.64) | (0.55) | | |
| Person-days worked (x1,000) | 306.49 | 41.04 | 0.03 | 17.42 | 0.716 | 561 |
| | [216.09] | (40.49) | (29.04) | (27.54) | | |
| Attendance registers (x1,000) | 5.52 | 0.68 | -0.20 | -0.43 | 0.672 | 561 |
| | [4.05] | (1.00) | (0.62) | (0.56) | | |
| Share of payment requests rejected | 0.09 | 0.00 | 0.02 | 0.03** | 0.084 | 550 |
| | [0.05] | (0.01) | (0.01) | (0.01) | | |
| *Panel B: District Supervisor Characteristics* | | | | | | |
| Age (years) | 42.47 | -1.29 | -0.72 | -1.71 | 0.883 | 129 |
| | [9.33] | (2.76) | (2.16) | (2.17) | | |
| Female | 0.14 | -0.09 | -0.16* | -0.12 | 0.323 | 132 |
| | [0.35] | (0.11) | (0.09) | (0.11) | | |
| Postgraduate completion | 0.84 | -0.03 | 0.02 | -0.18** | 0.130 | 134 |
| | [0.36] | (0.08) | (0.08) | (0.09) | | |
| Daily MIS usage | 0.96 | 0.11 | 0.11 | 0.06 | 0.398 | 68 |
| | [0.21] | (0.07) | (0.07) | (0.09) | | |
| Transfer subordinate for performance | 0.77 | 0.16 | -0.09 | -0.05 | 0.217 | 61 |
| | [0.42] | (0.13) | (0.17) | (0.16) | | |
| Knowledge gap | 0.38 | -0.21* | -0.17 | -0.22* | 0.219 | 122 |
| | [0.37] | (0.10) | (0.11) | (0.11) | | |
| Workload index | 0.00 | -0.01 | 0.09 | -0.12 | 0.670 | 134 |
| | [0.69] | (0.17) | (0.16) | (0.14) | | |
| Hours worked per week | 71.42 | 1.01 | 2.93 | 3.12 | 0.817 | 128 |
| | [16.63] | (4.04) | (3.83) | (3.89) | | |
| Calls per work day | 40.50 | 0.39 | 7.36 | -3.97 | 0.423 | 123 |
| | [24.39] | (5.29) | (6.79) | (4.73) | | |
| Additional charge | 0.44 | -0.06 | -0.13 | -0.16 | 0.544 | 118 |
| | [0.50] | (0.15) | (0.13) | (0.11) | | |
| *Panel C: Subdistrict Officer Characteristics* | | | | | | |
| Age (years) | 41.49 | 0.77 | 0.18 | 0.80 | 0.410 | 1009 |
| | [7.91] | (0.65) | (0.69) | (0.53) | | |
| Female | 0.16 | -0.03 | -0.01 | -0.03 | 0.794 | 1005 |
| | [0.36] | (0.04) | (0.04) | (0.04) | | |
| Postgraduate completion | 0.77 | -0.05 | -0.06* | -0.01 | 0.156 | 1011 |
| | [0.42] | (0.04) | (0.03) | (0.04) | | |
| Daily MIS usage | 0.93 | 0.04* | 0.02 | -0.02 | 0.053 | 987 |
| | [0.26] | (0.02) | (0.02) | (0.02) | | |
| Knowledge gap | 0.45 | 0.02 | -0.07 | -0.04 | 0.690 | 935 |
| | [0.80] | (0.10) | (0.07) | (0.07) | | |
| Workload index | 0.00 | 0.01 | 0.08 | 0.04 | 0.593 | 1023 |
| | [0.56] | (0.06) | (0.07) | (0.05) | | |
| Hours worked per week | 79.39 | 1.98 | 4.48** | 1.74 | 0.216 | 978 |
| | [17.64] | (1.82) | (2.10) | (2.01) | | |
| Calls per work day | 46.55 | 1.62 | 0.13 | 3.09 | 0.606 | 994 |
| | [27.14] | (2.89) | (3.30) | (2.51) | | |
| Additional charge | 0.30 | 0.04 | 0.12** | 0.04 | 0.100 | 1005 |
| | [0.46] | (0.04) | (0.05) | (0.04) | | |
| Irregular GRS contact | 0.26 | -0.08 | -0.08 | -0.05 | 0.396 | 1023 |
| | [0.44] | (0.05) | (0.06) | (0.05) | | |

Notes: For each row, column (1) presents variable means and standard deviations. Columns (2)-(4) present coefficients and standard errors from regressions on treatment arm indicators, randomization strata fixed effects, and, in Panels B and C, a program officer indicator. Column (5) gives the p-value from a joint test of zero-valued treatment arm coefficients. Standard errors are clustered by district in Panels B and C. Panel A variables are district- or subdistrict-level, generated from administrative data for the year before rollout (February 2016-January 2017) and 2011 census data. Panel B and C variables are district-officer- and subdistrict-officer-level, respectively, generated from baseline surveys.

Table A2: Additional Baseline Characteristics

| | Overall Mean | District Only | Subdistrict Only | Combination | Joint p-value | Obs |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Administrative Characteristics* | | | | | | |
| Days per working household | 12.76 | 0.45 | -0.86 | 0.12 | 0.612 | 561 |
| | [4.41] | (1.07) | (0.85) | (0.90) | | |
| Working households (x1,000) | 1.92 | 0.21 | 0.10 | 0.18 | 0.763 | 561 |
| | [1.17] | (0.22) | (0.18) | (0.22) | | |
| Standard deviation (days) | 15.23 | -0.95 | 1.22 | -0.19 | 0.309 | 561 |
| | [6.17] | (1.00) | (1.14) | (1.00) | | |
| Worker wage expenditure (x1,000,000 Rs.) | 48.98 | 4.81 | -0.64 | 2.27 | 0.830 | 561 |
| | [34.45] | (6.47) | (4.67) | (4.44) | | |
| *Panel B: District Supervisor Characteristics* | | | | | | |
| OBC/SC/ST | 0.45 | 0.01 | -0.19 | -0.14 | 0.243 | 130 |
| | [0.50] | (0.11) | (0.14) | (0.12) | | |
| Years government service | 16.27 | -6.21* | -1.40 | -2.20 | 0.372 | 100 |
| | [10.22] | (3.56) | (2.44) | (2.66) | | |
| Months in current post | 39.07 | 6.07 | 19.23*** | -0.08 | 0.020 | 105 |
| | [38.04] | (8.70) | (6.80) | (6.68) | | |
| All-India or state service | 0.53 | -0.13 | -0.11 | -0.13* | 0.298 | 118 |
| | [0.50] | (0.09) | (0.08) | (0.07) | | |
| Additional non-government job | 0.02 | -0.00 | -0.00 | 0.05 | 0.781 | 64 |
| | [0.12] | (0.02) | (0.02) | (0.05) | | |
| Monthly salary (x1,000 Rs.) | 50.32 | 12.06 | 8.56 | -1.41 | 0.790 | 69 |
| | [45.67] | (17.70) | (17.94) | (3.70) | | |
| Intrinsic motivation | 0.72 | -0.02 | 0.08 | 0.04 | 0.868 | 127 |
| | [0.45] | (0.15) | (0.11) | (0.10) | | |
| Locus of control | 0.78 | -0.12* | -0.05 | -0.10* | 0.158 | 121 |
| | [0.22] | (0.06) | (0.05) | (0.05) | | |
| Reciprocity | 2.44 | -0.10 | -0.07 | -0.04 | 0.754 | 126 |
| | [0.37] | (0.10) | (0.08) | (0.07) | | |
| Corruption propensity | 0.63 | -0.08 | -0.05 | 0.01 | 0.400 | 127 |
| | [0.25] | (0.06) | (0.07) | (0.06) | | |
| Big 5 | 0.01 | 0.05 | 0.08 | 0.07 | 0.896 | 136 |
| | [0.45] | (0.12) | (0.12) | (0.10) | | |
| PSM | -0.01 | 0.09 | 0.30* | 0.15 | 0.299 | 136 |
| | [0.65] | (0.17) | (0.16) | (0.16) | | |
| Raven's | 8.49 | 0.97 | 0.82 | 1.03 | 0.652 | 68 |
| | [2.77] | (1.00) | (0.88) | (0.89) | | |
| *Panel C: Subdistrict Officer Characteristics* | | | | | | |
| OBC/SC/ST | 0.65 | 0.02 | -0.01 | 0.01 | 0.966 | 991 |
| | [0.48] | (0.06) | (0.06) | (0.05) | | |
| Years government service | 14.90 | 0.78 | 0.10 | 0.80 | 0.440 | 917 |
| | [9.31] | (0.65) | (0.77) | (0.58) | | |
| Months in current post | 43.41 | -1.51 | -5.18 | -3.26 | 0.663 | 908 |
| | [47.16] | (4.81) | (4.50) | (3.67) | | |
| All-India or state service | 0.53 | 0.01 | -0.03* | -0.01 | 0.392 | 993 |
| | [0.50] | (0.03) | (0.02) | (0.01) | | |
| Additional non-government job | 0.00 | -0.00 | -0.00 | -0.00 | 0.568 | 918 |
| | [0.05] | (0.00) | (0.00) | (0.01) | | |
| Monthly salary (x1,000 Rs.) | 38.16 | 1.38* | -0.78 | 1.47** | 0.024 | 975 |
| | [16.66] | (0.75) | (1.01) | (0.63) | | |
| Intrinsic motivation | 0.62 | -0.05 | -0.02 | -0.00 | 0.638 | 967 |
| | [0.49] | (0.04) | (0.04) | (0.04) | | |
| Locus of control | 0.73 | 0.01 | -0.00 | 0.03* | 0.204 | 992 |
| | [0.22] | (0.02) | (0.02) | (0.02) | | |
| Reciprocity | 2.49 | 0.02 | 0.00 | 0.01 | 0.972 | 1001 |
| | [0.43] | (0.04) | (0.03) | (0.04) | | |
| Corruption propensity | 0.58 | 0.01 | 0.02 | 0.01 | 0.722 | 1005 |
| | [0.24] | (0.02) | (0.02) | (0.02) | | |
| Big 5 | 0.00 | -0.03 | 0.01 | 0.01 | 0.824 | 1023 |
| | [0.47] | (0.05) | (0.05) | (0.04) | | |
| PSM | 0.00 | -0.01 | -0.06 | -0.04 | 0.857 | 1023 |
| | [0.69] | (0.05) | (0.07) | (0.06) | | |
| Raven's | 8.61 | -0.14 | 0.26 | 0.44* | 0.144 | 960 |
| | [2.82] | (0.29) | (0.26) | (0.25) | | |

Notes: The first four variables are subdistrict-level monthly averages over the year before the intervention (February 2016-January 2017), generated from MGNREGS administrative data. See Table 1 notes and Appendix Section C.6 for additional details on table construction and officer personality/cognitive characteristics variables, respectively.

Table A3: Analysis Plan Deviations and Extensions

| Pre-specified approach | Deviation/Extension | Rationale |
|---|---|---|
| Dataset built by our team on an ongoing basis at the official-month level on PayDash access and the locality overseen each period. | Collected this information four times for Madhya Pradesh and three times for Jharkhand during the intervention. | In practice it was infeasible to collect this information monthly from each district for multiple officer categories. |
| Include officer previous year's income in the experimental balance table. | Replace with monthly salary. | Baseline survey not collect data needed for this variable. Monthly salary is closest available substitute. |
| Include summary of social networks (number of connections at each level, summary of frequency of interactions) – if piloted module yields usable data – in the experimental balance table. | Include share of local administrative units with which subdistrict-level officials in regular (weekly) contact. | Baseline survey collected information on contact occurring at weekly frequency. Focus on subdistrict officials given emphasis on workload at that level. |
| Examine impact on delays in payment processing times – both overall across steps under officer purview and by step. | Omit step-specific measures as outcomes. Examine total processing times and share processed within time ranges, including delayed vs not. | Unable to obtain data needed to generate step-specific measures. More informative to consider impacts not only in relation to official threshold. |
| In analysis, weight where relevant locality-month-level observations by the number of transactions (attendance registers) within each observation. Also consider specification with panchayat-month-level observations. | Not weight observations in primary analysis. Present weighted analysis results in Appendix Table A6 for relevant outcomes, both for subdistrict- and panchayat-month level observations. | Volume of attendance registers is itself potentially impacted by treatment, and maintain consistent specification across main outcomes. |
| Regression approach includes treatment indicators, subdistrict fixed effects, and month fixed effects. Also consider version with controls for district or subdistrict characteristics that may change over time for reasons unrelated to intervention. | Additionally consider version with pooled treatment indicator, and include district-specific controls for time trends in primary analysis. Present results of analysis excluding controls in Appendix Table A5. | Inclusion of pooled treatment version improves expositional clarity. In practice, lacked characteristics that able and appropriate to control for directly; use controls for time trends to account for chance differential changes over time. |
| Examine impacts on the number of person-days requested and worked, number of individuals worked, and total expenditure. | In place of person-days requested, use unmet demand measure from social audits data. Use working households rather than individuals. | Unable to identify source for person-days requested; unmet demand is closest available substitute. Data available for working households, not individuals. |
| Also examine officer management practices and information outcomes – e.g., payment timeline knowledge accuracy, performance incentive use, and contact network structure. | Consider officer posting transfers in relation to impacts on performance incentives, and omit contact network structure. | Unable to identify data sources on use of other performance incentives. Follow-up survey not collect needed information to examine impact on network structure. |
| | Main analysis outcomes also include: processing within time ranges (Figure 3, Tables 3–5); payment request rejection, days worked per household, and active worksites (Tables 3–5); and social audit outcomes (Table 6). | These outcomes capture impacts on additional dimensions of program performance or are informative of underlying mechanisms. In some cases, datasets allowing generation of these measures were only identified later. |
| | Bottom/top code values of non-categorical outcomes at 1st/99th percentiles of the control distribution. | Improve precision of estimates. |
| Main hypotheses regarding treatment impacts relate to district- and subdistrict-level PayDash, and complementarity between them. | Additionally hypothesize regarding substitutability between district and subdistrict PayDash. | We observed substitutability in impacts and collected information in follow-up surveys to examine underlying causes. |
| Examine treatment heterogeneity by officer administrative environment and cognitive/ personality characteristics. As part of latter, consider mean raw and standardized values for subcomponents of Big Five and Perry Public Service Motivation (PSM) measures. | For Big Five and PSM, use overall mean standardized value in Appendix Table A11 analysis. Also examine treatment heterogeneity by season (Tables 3–4). | Big Five and PSM each contain 4–5 subgroups; lack clear justification to examine subcomponents separately. Related literature highlights seasonality in program scale; relevant to bureaucrat bandwidth and effort allocation. |

Notes: Table lists and provides explanations for deviations from and extensions to our analysis plan, available at AEA RCT Registry entry AEARCTR-0001292.

Table A4: Bureaucrat Monthly PayDash Usage, Conditional on >0

| | Sessions | | Duration (min) | | Calls and messages | |
|---|---|---|---|---|---|---|
| | POs | CEOs | POs | CEOs | POs | CEOs |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Subdistrict Officers* | | | | | | |
| Subdistrict Only PayDash | 7.84 | 4.99 | 50.87 | 19.51 | 1.32 | 0.32 |
| | [10.19] | [7.68] | [112.15] | [47.87] | [11.78] | [2.29] |
| Both levels difference | 0.30 | 0.01 | -4.38 | -1.22 | 0.91 | -0.20** |
| | (1.14) | (0.85) | (10.03) | (2.99) | (1.24) | (0.10) |
| Observations | 1,641 | 1,104 | 1,641 | 1,104 | 1,641 | 1,104 |
| *Panel B: District Supervisors* | | | | | | |
| District Only PayDash | 10.24 | 2.74 | 61.99 | 9.50 | 40.01 | 0.74 |
| | [12.16] | [4.39] | [98.62] | [19.79] | [100.79] | [3.27] |
| Both levels difference | -4.05 | 1.68 | -37.41 | 5.87 | -33.30 | 0.53 |
| | (3.19) | (1.50) | (24.71) | (6.74) | (24.81) | (1.00) |
| Observations | 220 | 93 | 220 | 93 | 220 | 93 |

Notes: The first row in each panel reports means and standard deviations of each column's listed officer PayDash usage variable, calculated at the subdistrict-month (Panel A) or district-month (Panel B) level and restricted to treatment months in localities receiving PayDash only at the corresponding administrative level and with positive usage. Odd (even) columns consider usage by program (chief executive) officers. The second row of each panel shows the coefficient and standard error for an indicator for PayDash provision at both administrative levels from a regression of each column's listed usage variable on that indicator as well as month and strata fixed effects, restricted to treatment months in localities receiving PayDash at the corresponding administrative level and with positive usage. Standard errors clustered at the district level in parentheses. "Sessions" includes both web and mobile usage, and "Duration" captures mobile usage only. Significant at *10 percent, **5 percent,***1 percent.

Table A5: PayDash Impacts - Alternative Estimators

| | Log processing time (1) | Share processed "late" (>8 days) (2) | Absolute deviation (days) (3 | Share of payment requests rejected (4) | Log days per working household (5) | Log working households (6) | Log days worked (7) | Log active worksites (8) |
|---|---|---|---|---|---|---|---|---|
| *Panel A. TWFE* | | | | | | | | |
| Any PayDash | -0.078** | -0.042** | -0.133 | -0.011** | 0.061*** | -0.030 | 0.030 | -0.015 |
| | (0.033) | (0.016) | (0.231) | (0.004) | (0.021) | (0.064) | (0.070) | (0.073) |
| *Panel B. Callaway & Sant'Anna* | | | | | | | | |
| Any PayDash | -0.144*** | -0.087*** | -0.214 | -0.005 | 0.100** | 0.079 | 0.179* | 0.094 |
| | (0.036) | (0.018) | (0.281) | (0.003) | (0.041) | (0.069) | (0.096) | (0.075) |
| *Panel C. Sun & Abraham* | | | | | | | | |
| Any PayDash | -0.121*** | -0.081*** | -0.147 | -0.001 | 0.118*** | 0.078 | 0.196** | 0.075 |
| | (0.035) | (0.016) | (0.256) | (0.003) | (0.030) | (0.068) | (0.097) | (0.073) |
| With controls | -0.227*** | -0.113*** | -0.743** | -0.002 | 0.087** | 0.045 | 0.132 | 0.279*** |
| | (0.047) | (0.020) | (0.300) | (0.004) | (0.036) | (0.078) | (0.088) | (0.103) |
| *Panel D. de Chaisemartin & D'Haultfoeuille* | | | | | | | | |
| Any PayDash | -0.151*** | -0.089*** | -0.172 | -0.001 | 0.056** | 0.069 | 0.126** | 0.093 |
| | (0.048) | (0.023) | (0.224) | (0.004) | (0.024) | (0.053) | (0.064) | (0.067) |

Notes: Columns in Panel A report estimates following Equation (1) with controls for district-specific trends excluded. Columns in Panels B through D report estimates based on the Callaway and Sant'Anna (2021), Sun and Abraham (2021), and de Chaisemartin and D'Haultfoeuille (2024) estimators, respectively – averaging the estimated post-treatment period effects. Panel C additionally presents results from analysis including controls for district-specific trends, which is not possible for the analysis in Panels B and D. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A6: Processing Time Impacts - Weighting by Attendance Registers

| | Log processing time | | Share processed "late " (>8 days) | | Absolute deviation (days) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Any PayDash | -0.167*** | -0.161*** | -0.094*** | -0.086*** | -0.390* | -0.235* |
| | (0.039) | (0.037) | (0.018) | (0.017) | (0.212) | (0.123) |
| Observations | 13,443 | 564,597 | 13,443 | 565,108 | 13,443 | 565,108 |
| Subdistrict-month level | X | | X | | X | |
| Gram-panchayat-month level | | X | | X | | X |

Notes: Columns (1), (3), and (5) report estimates following Equation (1), weighting by the number of attendance registers within each subdistrict-month-level observation. Columns (2), (4), and (6) report estimates following a version of Equation (1) with gram panchayat fixed effects used in place of subdistrict fixed effects, weighting by the number of attendance registers within each gram-panchayat-month-level observation. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A7: PayDash Impacts - Additional Outcomes

| | Processing time (days) | Log attendance registers | Log register workspell length | Log worker wage expenditure | Worker composition: Below poverty line | Worker composition: Female |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Pooled Treatment* | | | | | | |
| Any PayDash | -1.739*** | 0.130* | -0.001 | 0.135** | 0.002 | 0.001 |
| | (0.388) | (0.076) | (0.007) | (0.064) | (0.001) | (0.002) |
| Control mean | 9.69 | 6.56 | 1.86 | 14.43 | 0.169 | 0.381 |
| Observations | 13,443 | 13,443 | 13,443 | 13,443 | 13,443 | 13,443 |
| *Panel B: Impact Seasonality* | | | | | | |
| Any PayDash × High season | 0.412* | 0.126** | 0.007 | 0.097** | -0.003* | 0.001 |
| | (0.235) | (0.048) | (0.008) | (0.043) | (0.001) | (0.002) |
| Any PayDash | -1.881*** | 0.076 | -0.004 | 0.093 | 0.003* | 0.001 |
| | (0.407) | (0.073) | (0.007) | (0.060) | (0.002) | (0.002) |
| Any+Any×High, p-value | 0.001 | 0.023 | 0.782 | 0.015 | 0.958 | 0.631 |
| Observations | 13,443 | 13,443 | 13,443 | 13,443 | 13,443 | 13,443 |
| *Panel C: Treatment Arms* | | | | | | |
| District Only PayDash | -1.915** | 0.211* | 0.002 | 0.233* | 0.003 | 0.004 |
| | (0.804) | (0.125) | (0.008) | (0.117) | (0.002) | (0.004) |
| Subdistrict Only PayDash | -1.990*** | 0.046 | 0.005 | 0.125 | 0.001 | -0.002 |
| | (0.489) | (0.088) | (0.008) | (0.067) | (0.003) | (0.003) |
| Combination PayDash | -1.421*** | 0.122 | -0.009 | 0.061 | 0.001 | -0.000 |
| | (0.531) | (0.100) | (0.011) | (0.077) | (0.002) | (0.004) |
| D + S = C, p-value | 0.015 | 0.402 | 0.222 | 0.036 | 0.558 | 0.690 |
| D = S = C, p-value | 0.673 | 0.500 | 0.442 | 0.367 | 0.702 | 0.436 |
| Observations | 13,443 | 13,443 | 13,443 | 13,443 | 13,443 | 13,443 |

Notes: Columns in Panel A report estimates following Equation (1). For each column, Panels B and C repeat the analysis in Panel A, including a high season indicator (not shown) and its interaction with the pooled treatment indicator in Panel B and replacing the pooled treatment indicator with treatment-arm-specific indicators in Panel C. Panel B also presents the p-value for the total MGNREGS high season impact of Any PayDash, and Panel C also presents p-values from tests of the equality of impacts across treatment arms ("D = S = C") and of the sum of the District Only and Subdistrict Only PayDash impacts with the Combination PayDash impact ("D + S = C"). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A8: PayDash Impacts - Inverse Propensity Weights

| | Payment processing | | | | Program scale | | | |
|---|---|---|---|---|---|---|---|---|
| | Log processing time | Share processed "late" (>8 days) | Absolute deviation (days) | Share of payment requests rejected | Log days per working household | Log working households | Log days worked | Log active worksites |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Any PayDash | -0.164*** | -0.085*** | -0.546** | -0.010*** | 0.088*** | -0.001 | 0.087 | 0.173*** |
| | (0.034) | (0.014) | (0.216) | (0.003) | (0.020) | (0.059) | (0.062) | (0.064) |
| Observations | 13,443 | 13,443 | 13,443 | 13,177 | 13,443 | 13,443 | 13,443 | 11,693 |

Notes: Columns report estimates following Equation (1), using inverse propensity score weighting. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A9: Heterogeneity by Real-time Data Availability

| | Log processing time (1) | Share processed "late" (>8 days) (2) | Absolute deviation (days) (3) |
|---|---|---|---|
| Any PayDash | | | |
| × Outage month MP | 0.099* | 0.052** | 0.418 |
| | (0.055) | (0.026) | (0.324) |
| × Lean season MP | 0.022 | 0.008 | 0.109 |
| | (0.038) | (0.016) | (0.169) |
| Any PayDash | -0.248*** | -0.110*** | -1.010*** |
| | (0.038) | (0.016) | (0.238) |
| Any + Any×Outage + Any×Lean, p-value | 0.074 | 0.106 | 0.233 |
| Observations | 13,443 | 13,443 | 13,443 |

Notes: All columns report estimates following Equation (1) additionally including interactions of indicators for the lean season and outage month in MP (which falls during the lean season) with the pooled treatment indicator as well as (not shown) outage-month and state-specific lean season indicators. Each column also presents the p-value for the total outage month impact of PayDash. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A10: Association of Administrative Structure and Workload

| | Workload index | | | |
|---|---|---|---|---|
| | Subdistrict officers | | District supervisors | |
| | (1) | (2) | (3) | (4) |
| GPs per subdistrict | 0.006** | | -0.006 | |
| | (0.003) | | (0.006) | |
| Subdistricts per district | -0.000 | | -0.001 | |
| | (0.007) | | (0.020) | |
| High GPs per subdistrict | | 0.101* | | 0.074 |
| | | (0.057) | | (0.135) |
| High subdistricts per district | | -0.005 | | 0.076 |
| | | (0.053) | | (0.138) |
| Outcome mean | 0.003 | 0.003 | -0.025 | -0.025 |
| Observations | 522 | 522 | 71 | 71 |

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

Table A11: Heterogeneity by Officer Characteristics

| | Log processing time | | | | | Log days per working household | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Attribute: | Raven's score | Locus of control | Corruption propensity | Big 5 | Perry PSM | Raven's score | Locus of control | Corruption propensity | Big 5 | Perry PSM |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *Panel A. District PO* | | | | | | | | | | |
| *i. Continuous* | | | | | | | | | | |
| Any PayDash | | | | | | | | | | |
| × Attribute | -0.020* | 0.092 | -0.084 | -0.051 | -0.030 | 0.005 | 0.023 | 0.045 | -0.014 | -0.001 |
| | (0.011) | (0.175) | (0.135) | (0.070) | (0.042) | (0.004) | (0.071) | (0.048) | (0.023) | (0.017) |
| Any PayDash | -0.010 | -0.243* | -0.128 | -0.177*** | -0.179*** | 0.053 | 0.074 | 0.064* | 0.093*** | 0.092 |
| | (0.096) | (0.132) | (0.084) | (0.036) | (0.035) | (0.044) | (0.055) | (0.036) | (0.017) | (0.017) |
| Observations | 12,651 | 12,699 | 12,963 | 13,155 | 13,155 | 12,651 | 12,699 | 12,963 | 13,155 | 13,155 |
| *ii. Above median* | | | | | | | | | | |
| Any PayDash | | | | | | | | | | |
| × Attribute | -0.141** | 0.058 | -0.079 | -0.055 | 0.041 | 0.056* | 0.037 | 0.032 | -0.026 | -0.007 |
| | (0.064) | (0.072) | (0.065) | (0.063) | (0.063) | (0.029) | (0.034) | (0.030) | (0.029) | (0.028) |
| Any PayDash | -0.094* | -0.218*** | -0.128** | -0.148*** | -0.204*** | 0.059** | 0.065** | 0.071*** | 0.107*** | 0.096*** |
| | (0.054) | (0.064) | (0.052) | (0.054) | (0.055) | (0.025) | (0.031) | (0.026) | (0.023) | (0.023) |
| Observations | 12,651 | 12,699 | 12,963 | 13,155 | 13,155 | 12,651 | 12,699 | 12,963 | 13,155 | 13,155 |
| *Panel B. Subdistrict PO* | | | | | | | | | | |
| *i. Continuous* | | | | | | | | | | |
| Any PayDash | | | | | | | | | | |
| × Attribute | 0.004 | 0.121** | -0.034 | -0.029 | 0.020 | 0.002 | 0.005 | -0.022 | -0.001 | -0.002 |
| | (0.005) | (0.051) | (0.071) | (0.030) | (0.023) | (0.003) | (0.031) | (0.041) | (0.014) | (0.010) |
| Any PayDash | -0.213*** | -0.262*** | -0.158*** | -0.175*** | -0.175*** | 0.080** | 0.091*** | 0.109*** | 0.098*** | 0.098*** |
| | (0.039) | (0.049) | (0.048) | (0.034) | (0.035) | (0.032) | (0.026) | (0.031) | (0.017) | (0.017) |
| Observations | 12,174 | 12,366 | 12,462 | 12,534 | 12,534 | 12,174 | 12,366 | 12,462 | 12,534 | 12,534 |
| *ii. Above median* | | | | | | | | | | |
| Any PayDash | | | | | | | | | | |
| × Attribute | 0.014 | 0.075** | 0.006 | -0.011 | 0.053* | 0.011 | -0.010 | -0.007 | -0.005 | -0.005 |
| | (0.029) | (0.030) | (0.031) | (0.025) | (0.029) | (0.018) | (0.015) | (0.018) | (0.013) | (0.016) |
| Any PayDash | -0.185*** | -0.224*** | -0.180*** | -0.170*** | -0.201*** | 0.090*** | 0.102*** | 0.101*** | 0.100*** | 0.100*** |
| | (0.032) | (0.039) | (0.035) | (0.038) | (0.037) | (0.021) | (0.019) | (0.022) | (0.018) | (0.020) |
| Observations | 12,174 | 12,366 | 12,462 | 12,534 | 12,534 | 12,174 | 12,366 | 12,462 | 12,534 | 12,534 |

Notes: Within each panel, all columns report estimates following Equation (1) with an additional interaction of the treatment indicator with the attribute listed in column header. The attribute is at the district PO level in Panel A and the subdistrict PO level in Panel B. The interaction is with a continuous version of the attribute in each sub-panel (i) and with an indicator for having an above-median value of the attribute in each sub-panel (ii). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent. See Appendix Section C.6 for variable construction details.

Table A12: Heterogeneity by Administrative Structure - Treatment Arms

| | Log processing time (1) | Share processed "late" (>8 days) (2) | Absolute deviation (days) (3) |
|---|---|---|---|
| District Only PayDash | | | |
| × High GPs per subdistrict | -0.275*** | -0.153*** | -0.792 |
| | (0.099) | (0.042) | (0.622) |
| District Only PayDash | -0.130** | -0.060*** | -0.619 |
| | (0.062) | (0.022) | (0.451) |
| Subdistrict Only PayDash | | | |
| × High GPs per subdistrict | -0.123* | -0.048 | -0.559 |
| | (0.070) | (0.031) | (0.499) |
| Subdistrict Only PayDash | -0.102** | -0.068*** | -0.295 |
| | (0.030) | (0.021) | (0.234) |
| Combination PayDash | | | |
| × High GPs per subdistrict | -0.070 | -0.033 | -0.532 |
| | (0.084) | (0.036) | (0.532) |
| Combination PayDash | -0.149* | -0.079** | -0.276 |
| | (0.075) | (0.030) | (0.476) |
| D + High×D, p-value | 0.000 | 0.000 | 0.001 |
| S + High×S, p-value | 0.002 | 0.000 | 0.064 |
| C + High×C, p-value | 0.000 | 0.000 | 0.008 |
| Observations | 13,443 | 13,443 | 13,443 |

Notes: Columns report estimates following Equation (3) additionally including interactions of the treatment arm indicators with an indicator for being an above-state-median district in terms of average number of panchayats per subdistrict ("high GP-ratio"). Columns also present p-values for the total MGNREGS impact of each treatment arm in high-GP-ratio areas. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A13: Heterogeneity by Administrative Structure - Including Interacted Controls

| | Payment processing | | | | Program scale | | | |
|---|---|---|---|---|---|---|---|---|
| | Log processing time | Share processed "late" (>8 days) | Absolute deviation (days) | Share of payment requests rejected | Log days per working household | Log working households | Log days worked | Log active worksites |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| High GPs per subdistrict × Any PayDash | -0.159** | -0.085*** | -0.687 | 0.001 | 0.013 | -0.068 | -0.055 | 0.075 |
| | (0.070) | (0.027) | (0.490) | (0.006) | (0.032) | (0.093) | (0.106) | (0.090) |
| Any PayDash | -0.070 | -0.051 | 0.499 | 0.003 | 0.084 | -0.212 | -0.128 | 0.048 |
| | (0.102) | (0.037) | (0.584) | (0.010) | (0.057) | (0.138) | (0.156) | (0.146) |
| Observations | 13,443 | 13,443 | 13,443 | 13,177 | 13,443 | 13,443 | 13,443 | 11,693 |

Notes: Columns report estimates following Equation (1) additionally including an interaction of the treatment indicator with an indicator for being an above-state-median district in terms of average number of panchayats per subdistrict ("High GPs-per-subdistrict"). Also included are interactions (not shown) of the treatment indicator with a Jharkhand state indicator and indicators for being an above-state-median district in terms of number of subdistricts, population, rural population share, and baseline average post-graduate education completion and daily MIS usage for subdistrict POs. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A14: Heterogeneity by Administrative Structure - Overall Median Measure

| | Payment processing | | | | Program scale | | | |
|---|---|---|---|---|---|---|---|---|
| | Log processing time | Share processed "late" (>8 days) | Absolute deviation (days) | Share of payment requests rejected | Log days per working household | Log working households | Log days worked | Log active worksites |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| High GPs per subdistrict × Any PayDash | -0.227*** | -0.093*** | -1.228** | 0.017* | -0.025 | 0.011 | -0.014 | 0.006 |
| | (0.072) | (0.031) | (0.497) | (0.010) | (0.045) | (0.110) | (0.141) | (0.116) |
| Any PayDash | 0.010 | -0.041 | 1.248* | -0.016 | 0.108* | -0.264** | -0.156 | 0.007 |
| | (0.102) | (0.045) | (0.689) | (0.011) | (0.064) | (0.123) | (0.154) | (0.133) |
| Observations | 13,443 | 13,443 | 13,443 | 13,177 | 13,443 | 13,443 | 13,443 | 13,177 |

Notes: All columns report estimates following Equation (1) with additional terms included as described subsequently. The analysis additionally includes interactions of the treatment indicator with indicators for being an above-median district in terms of average number of panchayats per subdistrict and (not shown) number of subdistricts, district-level measures of rural population share and log population, and the district-level baseline average post-graduate education completion and and daily MIS usage for subdistrict POs. Also included is an interaction of the treatment indicator with a Jharkhand state indicator. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A15: Impacts on Subdistrict Posting Transfers - Longer Term

| | Officer posting transfer (Madhya Pradesh) | |
|---|---|---|
| | 6 months | 17 months |
| | (1) | (2) |
| *Panel A: Pooled Treatment* | | |
| Any PayDash | -0.045 | -0.079 |
| | (0.062) | (0.050) |
| Control mean | 0.660 | 0.773 |
| Observations | 616 | 616 |
| *Panel B: Treatment Arms* | | |
| District Only PayDash | -0.118* | -0.123* |
| | (0.069) | (0.063) |
| Subdistrict Only PayDash | 0.054 | -0.012 |
| | (0.069) | (0.058) |
| Combination PayDash | -0.049 | -0.088 |
| | (0.074) | (0.061) |
| D + S = C, p-value | 0.873 | 0.593 |
| D = S = C, p-value | 0.026 | 0.167 |
| Observations | 616 | 616 |

Notes: Columns in Panel A report estimates from regressions at the subdistrict-position level of the listed variable on a pooled treatment indicator as well as strata fixed effects and a program officer indicator. Panel B repeats the analysis in Panel A, replacing the pooled treatment indicator with treatment-arm-specific indicators. The table also presents p-values from tests of the equality of impacts across treatment arms ("D = S = C") and of the sum of the District Only and Subdistrict Only PayDash impacts with the Combination PayDash impact ("D + S = C"). The sample is restricted to observations in Madhya Pradesh, for which the 17-month measure can be generated. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A16: Audit Impacts - Index Components

| | Index components | | | |
|---|---|---|---|---|
| | Any financial deviation | Any financial misapprop. | Any grievance | Any process violation |
| | (1) | (2) | (3) | (4) |
| *Panel A: Pooled Treatment* | | | | |
| Any PayDash | -0.011 | -0.006 | -0.011 | -0.009 |
| | (0.025) | (0.015) | (0.019) | (0.035) |
| Control mean | 0.122 | 0.102 | 0.135 | 0.192 |
| Observations | 20,621 | 20,621 | 20,621 | 20,621 |
| *Panel B: Treatment Arms* | | | | |
| District Only PayDash | 0.004 | 0.004 | -0.007 | 0.010 |
| | (0.027) | (0.017) | (0.026) | (0.043) |
| Subdistrict Only PayDash | -0.011 | -0.010 | -0.002 | -0.017 |
| | (0.025) | (0.015) | (0.022) | (0.035) |
| Combination PayDash | -0.026 | -0.012 | -0.024 | -0.019 |
| | (0.025) | (0.016) | (0.019) | (0.037) |
| D + S = C, p-value | 0.508 | 0.740 | 0.626 | 0.797 |
| D = S = C, p-value | 0.074 | 0.279 | 0.412 | 0.599 |
| Observations | 20,621 | 20,621 | 20,621 | 20,621 |

Notes: Columns in Panel A report estimates from regressions at the audit level of the listed variable on a pooled treatment indicator and strata fixed effects. Panel B repeats the analysis in Panel A, replacing the pooled treatment indicator with treatment-arm-specific indicators and also presenting p-values from tests of the equality of impacts across treatment arms ("D = S = C") and of the sum of the District Only and Subdistrict Only PayDash impacts with the Combination PayDash impact ("D + S = C"). "Any financial misapprop." is an abbreviation of "Any financial misappropriation". Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

# Appendix B: Model - Principal's Problem

## B.1 No rent-seeking by manager

We start with the case where the manager's effort choice is solely determined by effort costs. Under contract $L$, the principal sets $\underline{w} = 0$. Under contract $H$, the principal sets $w_0 = 0$. Contracts where the principal wants to induce $e_M = 1$ are as follows:

$$w_H = w_H(Y) = \begin{cases} 0, & Y = 0 \\ \frac{c_M}{\pi_1 - \pi_0}, & Y = Y_1 \end{cases} \quad \text{and} \quad w_L = w_L(e_M) = \begin{cases} 0, & e_M = 0 \\ c_M, & e_M = 1 \end{cases}$$

The principal's expected payoffs for each contract-effort pair are below, with the columns indicating contract $I \in \{H, L\}$ and the rows indicating manager effort induced.[37]

| | $H$ | $L$ |
|---|---|---|
| $e_M = 0$ | $\pi_0 Y_1$ | $\pi_0 Y_1 - c_P$ |
| $e_M = 1$ | $\pi_1 \left[Y_1 - \frac{c_M}{\pi_1 - \pi_0}\right]$ | $\pi_1 Y_1 - c_P - c_M$ |

The first result characterizes equilibria $(I, e_M)$ given the cost parameters $(c_M, c_P)$.

**Theorem 1.** *The equilibrium $(I, e_M)$ is characterized as follows:*

- $(H, 1)$ *is optimal for* $c_M \leq \min\left\{\frac{c_P(\pi_1 - \pi_0)}{\pi_0}, \frac{Y_1(\pi_1 - \pi_0)^2}{\pi_1}\right\}$
- $(L, 1)$ *is optimal for* $c_P \leq \min\left\{\frac{c_M \pi_0}{\pi_1 - \pi_0}, (\pi_1 - \pi_0)Y_1 - c_M\right\}$
- $(H, 0)$ *is optimal for* $c_M \geq \max\left\{\frac{Y_1(\pi_1 - \pi_0)^2}{\pi_1}, (\pi_1 - \pi_0)Y_1 - c_P\right\}$

We characterize the pre-PayDash status quo as having sufficiently high $c_M$ and $c_P$.[38] Corollary 1 specifies the impact of PayDash, and Figure B1 summarizes how contract and manager effort change with costs for the manager and principal.

**Corollary 1.** *If PayDash generates sufficient reductions in $c_P$ and $c_M$ when provided to the principal and manager, respectively, the following hold.*

[37] We assume that the manager exerts effort when indifferent to doing so.

[38] Specifically, $\frac{Y_1(\pi_1 - \pi_0)^2}{\pi_1} \leq c_M \leq Y_1(\pi_1 - \pi_0)$ and $c_P \geq \frac{Y_1 \pi_0 (\pi_1 - \pi_0)}{\pi_1}$.

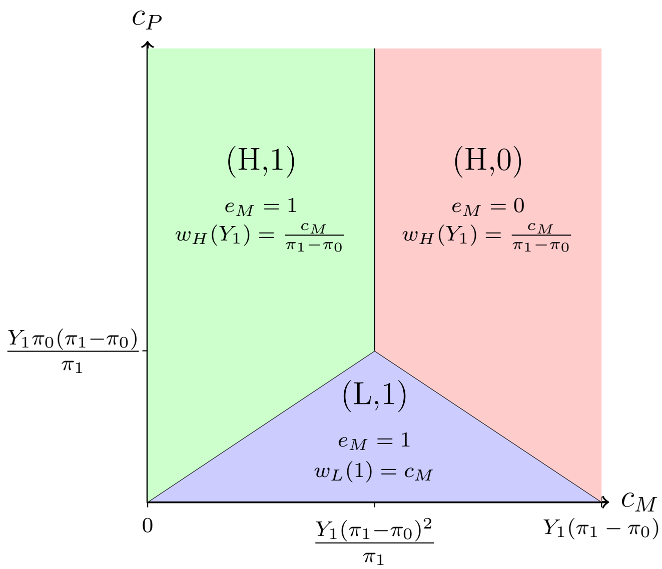



Figure B1: Equilibrium contracts with varying $c_M, c_P$

1. *(**Substitutability**) The impact of PayDash on manager effort, $e_M$, is the same whether provided to principal, manager, or both.*

2. *(**Program implementation**) Provision of PayDash to principal, manager, or both increases expected output.*

3. *(**Manager transfers**) Provision of PayDash to the principal alone or both the principal and manager decreases expected transfers by (weakly) more than provision to the manager alone.*

Note, for small enough respective reductions in $c_P$ and $c_M$ when PayDash is provided to the principal and manager, it can be that changes in contract structure and manager effort occur only when PayDash is provided at both levels – i.e., principal and manager PayDash are complements.

## B.2 Rent-seeking by the manager

We model manager collusion with frontline agents to extract rents as her receiving a direct benefit from shirking. Specifically, she receives benefit $K > 0$ from effort $e_M = 0$.

Consider high-powered contract $H$ where $w_H$ is conditioned on output $Y$. The manager's expected payoffs depending on effort are:

$$\pi_1 w_H(Y_1) - c_M, \quad \text{for} \quad e_M = 1$$
$$\pi_0 w_H(Y_1) + K, \quad \text{for} \quad e_M = 0$$

and the principal uses $w_H(Y_1) = \frac{c_M + K}{\pi_1 - \pi_0}$ to incentivize effort.

Consider low-powered contract $L$ where $w_L$ is conditioned on on effort $e_M$. The manager's expected payoffs depending on effort are:

$$w_L(1) - c_M, \quad \text{for} \quad e_M = 1$$
$$w_L(0) + K, \quad \text{for} \quad e_M = 0$$

and the principal uses $w_L = c_M + K$ to incentivize effort.

**Theorem 2.** *With a corrupt manager, the equilibrium $(I, e_M)$ is characterized as follows:*

- *(H,1) is optimal for $c_M \leq \min\left\{\frac{c_P(\pi_1-\pi_0)}{\pi_0} - K, \frac{(\pi_1-\pi_0)^2 Y_1}{\pi_1} - K\right\}$*
- *(L,1) is optimal for $c_P \leq \min\left\{\frac{(c_M+K)\pi_0}{\pi_1-\pi_0}, (\pi_1-\pi_0)Y_1 - c_M - K\right\}$*
- *(H,0) is optimal for $c_M \geq \max\left\{\frac{Y_1(\pi_1-\pi_0)^2}{\pi_1} - K, (\pi_1-\pi_0)Y_1 - c_P - K\right\}$*

We characterize the pre-PayDash status quo as having $K \in \left[\frac{(\pi_1-\pi_0)^2}{\pi_1}Y_1, (\pi_1-\pi_0)Y_1\right]$ and $c_M$ and $c_P$ sufficiently high.[39] Corollary 2 specifies the impact of PayDash in the corrupt manager setting, and Figure B2 shows for an example value of K how contract and manager effort change with costs for the manager and principal.

**Corollary 2.** *If PayDash generates sufficient reductions in $c_P$ and $c_M$ when provided to the principal and manager, respectively, the following hold.*

1. *(**Sufficiency**) An increase in manager effort is generated by provision of PayDash to the principal alone or both the principal and manager, but not the manager alone.*

2. *(**Program Implementation**) An improvement in expected output results from provision of PayDash to the principal alone or both the principal and manager, but not the manager alone.*

[39]Specifically, $c_P \geq \frac{Y_1\pi_0(\pi_1-\pi_0)}{\pi_1}$ and $\frac{Y_1(\pi_1-\pi_0)^2}{\pi_1} - K \leq c_M \leq (\pi_1-\pi_0)Y_1 - K$

3. (***Manager transfers***) *Expected transfers decrease with provision of PayDash to the principal alone or both the principal and manager, but not the manager alone.*

Note, for $K$ "too large" (above the previously specified range), the principal will always find it too costly to induce manager effort, and, for $K$ "too small" (below the previously specified range), decreasing $c_M$ enough will alone induce the manager to exert effort.

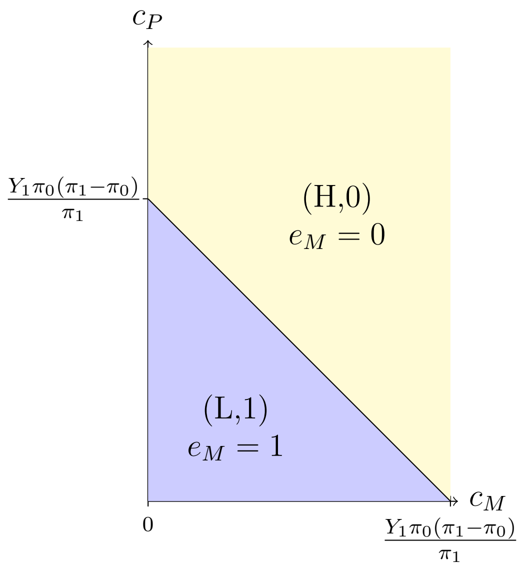



Figure B2: Equilibrium contracts under corruption, with $K = \frac{Y_1(\pi_1-\pi_0)^2}{\pi_1}$

# Appendix C: Additional Details

## C.1 Randomization strata

The district-level average processing time measure used in defining the randomization strata was calculated across attendance-register-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-subdistrict volume of person-days worked measure used was the average of the subdistrict-level monthly totals of person-days worked across subdistricts 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.

## C.2 PayDash training

To provide the MNGREGS MIS refresher training and introduce treated bureaucrats to PayDash, we invited the relevant bureaucrat – district and subdistrict CEOs and POs – in each training session catchment area to a half-day session. To avoid treatment contamination, treatment area bureaucrats were trained on separate days and/or locations from those in control areas. To avoid sensitivities related to bureaucrats' seniority differences, we conducted sessions separately for treatment and control bureaucrats by subdistrict and district levels.

First, we collected baseline survey data from all bureaucrats through a self-administered, paper survey. We then conducted a session outlining available data-based management tools in the MGNREGS MIS and asked bureaucrats to share their professional challenges. This ended the training for control bureaucrats. In sessions with treatment bureaucrats, the training continued with an additional one-hour session on PayDash. This included downloading the app and conducting preliminary exercises on the platform to ensure it was functional and they understood how to use it.

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 bureaucratss to report for this training) to maximize attendance at the training sessions. For bureaucrats that did not attend the group-based training, we subsequently conducted individual surveying and onboarding to PayDash (when relevant).

## C.3 Social audits

Social audits are community (GP)-level exercises intended to assess the quality of local MGNREGS delivery, with the aim of strengthening accountability and improving program implementation. The central government has outlined audit guidelines, while states decide where and when to conduct audits. In Jharkhand, GPs were randomly selected 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 district-level hearings intended to resolve larger issues. In Madhya Pradesh, the state selected subdistricts to be audited within a given fiscal year. Targeted subdistricts were rotated to maximize audit location coverage across years. GPs within the same subdistrict were targeted to be audited within the same quarter. We observe that GP audit probability does not differ significantly by district treatment status.

Audits last roughly one week and include visits by independent auditors from outside the community to households listed as having worked in 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. Audits typically have an 11-month reference period. 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 submit a formal audit report. The reports include issues raised and filed in the Gram Sabha, as well as an audit checklist that records the observations made by the auditors during visits to 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.

## C.4 Table 1 response category definitions

In Panel A of Table 1, "Lack of work" is "unavailability of MGNREGS work"; "low wage" is "MGNREGS wage rate is lower than market"; "poor work conditions" is "inability to work for creation of specific assets because of uncomfortable work conditions"; "payment delays" is "delays in payments reaching bank accounts"; "unable access money from bank" is "inability to access MGNREGS payments that have been deposited into bank account"; "corruption" is "corruption in MGNREGS implementation"; and "hard to contact GP officials" is "difficulty in contacting MGNREGS officials".

In Panel B, "inadequate work demand" is "inadequate demand registration due to factors such as low motivation and payment delays"; "IT infrastructure" is "infrastructural issues such as poor internet connectivity and power shortages"; "inadequate manpower" is "inadequate manpower (GRS, engineer, etc.) to manage the scheme"; "inability to contact GP officials" is "inability to contact GP-level MGNREGS officials"; "lack power to take action" is "lack of administrative power to take action against officials involved in MGNREGS implementation"; "corruption" is "corruption in MGNREGS implementation"; "process requirements" is the highest rank of "maintenance of 60:40 wage-material ratio" and "unrealistic targets in labor budget"; and "bank payment delays" is "payment delays from the banks' end".

In Panel C, "administrative malpractice" is "complaints regarding administrative malpractice"; "work provision" is the highest rank of "achievement of labor budget targets", "generation of person-days", and "work provided as percentage of work demanded"; "asset production" is the highest rank of "work completion rate", "percentage of works running as per schedule", and "quality and type of assets under construction"; "priority group participation" is the highest rank of "SC/ST participation" and "female participation"; "payment delays" is "payment delays"; and "expenditure category distribution" is the highest rank of "maintenance of 60:40 wage-material ratio" and "60% allocation of expenditure to agriculture and allied activities".

## C.5 Benefit-Cost Analysis

For our benefit–cost analysis of PayDash, we first estimate benefits to workers due to improvements in wage payment delivery times. We take the estimated 16.6% (18.1 log point) PayDash-driven reduction in Stage-I processing time and apply it to the control group mean, giving a 1.38-day reduction and corresponding 1.3-day pass-through drop in final time to payment. Based on this impact, we assume that households reduce workspell-associated loan size by an amount equal to one day of needed consumption and that time to loan repayment drops by one day.

To estimate the loan size needed to finance one day of household consumption, we utilize Reserve Bank of India (RBI)-issued rural poverty lines for Madhya Pradesh and Jharkhand, computing the per capita daily poverty threshold for households' basic consumption needs. We estimate this need by assuming the average rural household in these states had 4.1 members, based on data in the 2017-2018 Periodic Labour Force Survey, for respondents in the bottom two expenditure quintiles for rural Jharkhand and Madhya Pradesh. We then inflate the official RBI 2012 poverty line to 2017 values using the official consumer price index for rural India for February 2017 (the first month of intervention roll-out) as reported by the RBI.[40] This gives a $2.12 estimated daily cost of household consumption (and PayDash-driven reduction in loan principal), where all INR amounts in our analysis are converted to USD using the average exchange rate of 65.1 INR per USD over the time period of the intervention, based on values used for project cost conversion as reported by J-PAL South Asia.

To estimate the average loan interest rate, we use data from the All-India Debt and Investment Survey for 2019, as collected in India's National Sample Survey (NSS). We base our assumed interest rate on the values associated with loans that respondents reported taking in the 2017 and 2018 calendar years. Specifically, we use the terms of loans from professional moneylenders used for non-business purposes, restricting to households in Jharkhand and Madhya Pradesh who reported securing short-term loans in these two years.[41] To better match the MGNREGS worker population, we further restrict focus to loan terms for house-

[40] This information is available at the government website here.

[41] The survey captures loan tenure, so we restrict to the shortest tenure category – one-year duration or less.

holds in the bottom two quintiles of consumption expenditure. The majority of these loans report a simple interest structure, so we assume the same for the average loan interest rate, 34%. Based on observed average Stage-I processing time in control areas and assumptions that banks take the full time allotted for Stage-II processing and that workers repay loans as soon as they receive associated workspell payment, we assume a sixteen-day status quo loan repayment length.

Combining the above values yields \$0.06 saved per loan and – given roughly 3,280 affected loans per subdistrict-month implied by the observed monthly numbers of working households and workspells per household – approximately \$200 in interest saved per subdistrict-month. Next, we calculate the total amount of additional wages paid to workers as a result of PayDash access. Using the 2017-18 MGNREGS official worker daily wage rates of 168 and 172 INR for Jharkhand and Madhya Pradesh, respectively, in combination with the estimated PayDash-induced increase of roughly 1,700 person-workdays per subdistrict-month, yields an increase of more than \$4,400 in wages to poor rural households per subdistrict-month.[42] Our study states have 578 subdistricts, which we use when calculating scaled annual values.

To assess PayDash costs, we utilize actual project expenditure data. Relevant only to the first year of implementation, a total of \$98,420 was spent on PayDash app development and testing, and \$37,139 on initial roll out and training. Additional annual costs which would be incurred beyond the first year include \$35,658 for app maintenance and oversight, as well as \$10,971 for user transfer tracking, access updating, and new user onboarding. As PayDash was rolled out in 53 of 75 districts (excluding 20 control districts and 2 pilot districts) during our randomized evaluation, we correspondingly upscale the yearly tracking and retraining costs to account for coverage of all areas. Since our intervention included in-person surveying and training of all relevant subdistrict and district officers on MIS tools in addition to providing a one-hour PayDash training to treated officers (the combined cost of which is greater than that of simply providing PayDash training to all officers), we do not apply this upscaling to the initial roll out and training costs. This gives an estimated first year total at-scale cost of \$186,742, and annual cost in subsequent years of \$51,184.

To examine the benefits and costs for the comparison scenario of hiring additional subdis-

[42]State-wise unskilled worker wage rate data is available at the government MGNREGS website here.

trict officers, we first take the mean \$367 value of reported monthly salary for subdistrict-level Program Officers in our baseline survey. We further include in costs the average reported phone and data-related expenses, \$31 per month, covered by the state. We assume these hires entail no commitment beyond a single year and no additional associated costs. To estimate the number of additional subdistrict officers needed to reduce time to payment in line with the PayDash impact, we use the association between log processing time and average number of GPs overseen by subdistrict officials in control districts, based on which each additional GP overseen is associated with .035 more days of payment processing time. To achieve the same reduction in payment delivery time estimated for PayDash, subdistrict officers would then need to oversee 40 fewer GPs on average (in comparison with their current average oversight of 47 GPs per subdistrict; Appendix Table A1). We assume that at the time of the intervention, all 578 subdistricts in our study states had one Subdistrict PO, with these subdistricts covering 27,243 GPs. To achieve the needed reduction in average GPs per subdistrict officer, each subdistrict would need to hire 5.33 officers on average. Based on the baseline salary and mobile data costs, these 3,081 additional officials would cost nearly \$15 million per year across both states. We assume the same benefits from additional staffing as for PayDash provision, so relative benefit-cost results follow directly.

## C.6 Appendix Table A11 officer characteristic variables

In Panel A:

- The Raven's score variable is the number of correct answers given to a sequence of twelve Raven's matrices questions successively increasing in difficulty.
- The locus of control variable is the average score across the following four comparisons, where value 1 is given for choosing the first statement in each pair and 0 for choosing the second: {What happens to me is my own doing; Sometimes I feel that I don't have enough control over the direction my life is taking}, {When I make plans, I am almost certain I can make them work; It is not always wise to plan too far ahead, because many things turn out to be a matter of good or bad fortune anyhow}, {In my case, getting what I want has little or nothing to do with luck; Many times we might just

as well decide what to do by flipping a coin}, {It is impossible for me to believe that chance or luck plays an important role in my life; Many times I feel that I have little influence over the things that happen to me}.

- The corruption propensity variable is the average score based on level of agreement with the following three statements: the amount of pay you receive in your position accurately reflects the amount of work you do in your job (1: disagree/strongly disagree, 0: agree/strongly agree); success is determined more by "who you know" than by "what you know" (1: agree/strongly agree, 0: disagree/strongly disagree); promotions should be based primarily on job performance rather than seniority (1: disagree/strongly disagree, 0: agree/strongly agree).

- The Big Five variable is the average standardized value (based on underlying one to five scores corresponding to levels of agreement ranging from strongly disagree to strongly agree, respectively; when indicated, the score to agreement type mapping is reversed) across the following ten statements related to agreeableness, conscientiousness, extroversion, emotional stability, and openness: Some people think that I am selfish and egoistic (scoring reversed); I am mistrustful and skeptical about the intentions of others (scoring reversed); I am not a very organized person (scoring reversed); I work very hard to achieve my goals; I like to be amongst lots of people; I am a jolly and optimistic person; I often feel mentally stressed and anxious (scoring reversed); I often feel helpless and wish someone else would resolve my problems (scoring reversed); I don't pay much attention to the moods and feelings evoked by my surroundings and circumstances (scoring reversed); and I have a lot of intellectual curiosity in me.

- The Perry PSM (Public Service Motivation) variable is the average standardized value (based on underlying one to five scores corresponding to levels of agreement ranging from strongly disagree to strongly agree, respectively) across the following sixteen statements related to attraction to public service, commitment to public values, compassion, and self sacrifice: I admire people who initiate or are involved in activities to aid my community; It is important to contribute to activities that tackle social problems; Meaningful public service is very important to me; It is important for me to contribute to the common good; I think equal opportunities for citizens are very important; It is important that citizens can rely on the continuous provision of public services; It is fundamental that the interests of future generations are taken into account when developing public policies; To act ethically is essential for public servants; I feel sympathetic to the plight of the underprivileged; I empathize with other people who face difficulties; I get very upset when I see other people being treated unfairly; Considering the welfare of others is very important; I am prepared to make sacrifices for the good of society; I believe in putting civic duty before self; I am willing to risk personal loss to help society; and I would agree to a good plan to make a better life for the poor, even if it costs me money.

In Panel B, the variables are indicators for being above-median within bureaucrat type in terms of the value of each variable included in Panel A. All variables come from survey baseline.