Can Reducing Information Frictions Strengthen State Capacity? Experimental Evidence from a Very Large Public Works Program

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Abstract

In low state capacity environments, improved information flows can aid program implementation by bureaucrats managing heavy workloads. However, if incentives across the administrative hierarchy are not aligned, implementation improvements can vary with who receives the information. To assess if and why easier information access affects program implementation quality, we collaborated with two Indian states to randomly assign which bureaucrats had access to "PayDash", a digital platform that made it easier to track and process payments for rural workfare workers. Social protection strengthened in districts with PayDash access: Worker payment processing times fell by 24% and participating households worked 9% more. During the agricultural lean season, overall work provision increased. PayDash has similar impacts whether assigned to principals or managers, with no additional gains when offered to both, indicating that effort costs, rather than managerial rent-seeking, constrain implementation in understaffed bureaucracies. Consistent with easier information access enabling adoption of incentive contracts that condition managerial incentives on measures of effort and not just final program outcomes, PayDash for principals reduced costly manager posting transfers by 20%. Increased work days and reduced wage payment delays accruing through PayDash

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provision strengthened state capacity, benefiting rural Indians at a rate roughly fifty times that of costs.

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1 Introduction

The effectiveness of delegated governance depends on the quality of information flows within the organization: Principals and managers need accurate information to supervise their subordinates (Aghion and Tirole 1997; Dixit 2002; Mookherjee 2006). Governments' increasing use of digital fund-flow management systems opens up opportunities to utilize digital exhaust to improve information flows inside implementing public agencies, especially in lower state-capacity settings.[1] However, the impact of improving information flows within an organization on bureaucratic performance depends on the nature of the underlying friction: Was getting information too costly for overworked bureaucrats, or was information available to managers but being used to extract rents rather than improve program performance?

Consider a stylized representation of the bureaucratic structure tasked with implementing social protection programs, which includes a principal, a manager, and frontline personnel. Lowering a manager's information acquisition costs can directly improve program performance if her knowledge of frontline implementation challenges is limited. However, if the manager's rent-seeking is the relevant friction, enhancing the principal's information is critical, and doing so solely for managers may backfire (Khan et al. 2019). Separately, if the principal's goal in structuring managerial incentive contracts is to minimize her effort costs, improving her information can have the added benefit of increasing the likelihood that negative incentives, like transferring bureaucrats out of their posts, is conditioned on manager effort rather than realized program outcomes (Iyer and Mani 2012; Carroll and Bolte 2023).

To estimate how lowering information acquisition costs for bureaucrats impacts program implementation, we conducted a large-scale experiment with bureaucrats who implement India's workfare program, the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS), in two North Indian states, Madhya Pradesh and Jharkhand. More than 50 million households across India participated in MGNREGS in 2017-18 (the year of our intervention), earning over USD 6 billion.[2] Multiple studies show positive program impacts on participating households' well-being (Imbert and Papp 2015; Deininger and Liu 2019; Klon-

[1]For instance,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. E.g., 63% of COVID-related transfers in lower-income countries occurred through digital infrastructure.

[2]Districts are the highest within-state administrative unit. District-based bureaucracies manage state-level MGNREGS implementation. District officers function as program principals and manage subdistrict officers. Subdistrict officers, in turn, authorize MGNREGS worker payments and oversee frontline officials who select workers, implement program works, and collect work completion data.

ner and Oldiges 2022; Muralidharan et al. 2023). However, payment delays often undermine MGNREGS' premise of helping households smooth income and consumption (?Basu et al. 2024), reducing the value of program participation and increasing reliance on alternative coping strategies that risk exploitation (Narayanan et al. 2017; Dréze 2020). Delays may also reduce program demand by citizens.

Our intervention included over 1,200 MGNREGS bureaucrats working across 73 districts and 561 subdistricts and ran from February 2017-August 2018.[3] Districts were randomly assigned to control or one of three treatment groups where subdistrict officials (managers), their district-level supervisors (principals), or both received PayDash, a mobile- and web-based application that tracks 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 effort costs in obtaining information on program implementation.

We report four sets of findings. First, Google Analytics data demonstrate that officers 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, implies that officers used PayDash to gain *real-time* implementation information. Usage levels recovered once the data outage was resolved.

Second, using data from 17.4 million MGNREGS attendance registers from the intervention and preceding year, we show that bureaucrats in PayDash districts process payments 24% faster and with less variability than in control districts. This translates into 2.6 fewer days for bureaucratic payment processing.[4] Treatment districts also show a 9% increase in person-days worked by participating households, which translates into 390 additional person-days worked per subdistrict-month. While treatment-induced improvements in payment processing are similar throughout the year, treatment effects on work activity, including days worked and the number of active worksites, are concentrated in the MGNREGS high season, when work opportunities are otherwise most limited for vulnerable households.

Our third set of findings exploits experimental variation in the level of administrative hierarchy that received PayDash. If the underlying friction is high program information acquisition costs, PayDash provision across levels will be substitutes. If managers use information to col-

[3]Start date varied by state: February 2017 for Madhya Pradesh and October 2017 for Jharkhand.

[4]Payments took 10 extra days on average to complete beyond the government's mandated 8-day limit in control. Payment processing time is highly correlated (0.82) with time to final payment delivery, which also includes banks handling government payment orders and disbursing funds to worker accounts.

lude with frontline workers and extract rents, PayDash-induced program improvements will not be realized unless principals receive PayDash. We observe statistically indistinguishable impacts on program outcomes regardless of the level of hierarchy at which PayDash is provided. This is consistent with improved information enabling better program implementation. Using quasi-experimental variation in sub-district officer workload (due to differences in the number of villages they oversee), we show that PayDash induced program gains are concentrated in higher workload districts, where easier access to information is likely to be especially valuable.

Our fourth set of findings concerns officer-level outcomes. Bureaucratic posting transfers are a standard method used by district officers to punish poor subdistrict officer performance. According to theory, better information about manager actions should allow the principal to condition incentives on managerial effort measures rather than solely on final program outcomes. Knowing when payment delays reflect frontline issues beyond the manager's control versus delays in when the manager submits invoices, for example, allows the principal to punish the manager only in the latter scenario. Consistent with better targeting of incentives, PayDash reduces the use of costly managerial transfers by 10 percentage points (23%). Transfers are unaffected when only managers receive PayDash. Our final sets of evidence corroborate our experimental results, pointing to the direct impact of better information on program implementation. Specifically, we observe no PayDash impact on program implementation irregularities, including financial misappropriation, detected during external audits. And, endline officer surveys show that PayDash improves managers' accuracy in assessing payment processing performance by 19%, with similar impacts across treatment arms. Additionally, treated principals report sharing PayDash information with managers.

PayDash is highly cost-effective: We calculate the benefits accruing to low-income households as the sum of averted loan costs —avoided because impoverished households receive safety net payments more quickly and thus can avoid the costs of consumption loans while awaiting payment —and improved access to MGNREGS work. Our back-of the-envelope calculation shows that these benefits are 49 times the platform development and maintenance costs in the first year alone. In subsequent years, when development costs are significantly lower, the benefits exceed the annual maintenance cost by 100 times.

Our paper contributes to a growing literature on how e-governance reforms to MGNREGS implementation affect program outcomes. The literature primarily focuses on e-governance reforms that reduce administrative responsibilities, such as in payment delivery (Muralidharan et al. 2016) and fund flow approval (Banerjee et al. 2020). These reforms have been shown to reduce funds leakage. While citizen facing reforms improve program outcomes, simply eliminating administrative responsibilities for funds flow does not. We show that, holding organizational structure constant, e-governance can improve MGNREGS implementation when it aids lowering of information frictions across bureaucrats. The broaderliterature on how information frictions impact service delivery in lower-income countries has largely focused on the effectiveness of top-down monitoring in disciplining lower-level government workers (Banerjee et al. 2008; Duflo et al. 2012; Dhaliwal and Hanna 2017; Finan et al. 2017); other recent research emphasizes the importance of information for middle managers (Dal Bó et al. 2021). Our contribution is an experimental comparison of the implications of improving information access at different levels of the bureaucratic hierarchy.[5]

In demonstrating that reducing bureaucrats' information acquisition costs is more beneficial in areas where they face higher workloads, we connect to a literature that shows under-resourcing is common in lower-income countries' limited capacity administrative contexts and can harm 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 (Aman-Rana and Minaudier 2024).

The paper is organized as follows: Section 2 provides context and uses a simple conceptual framework to motivate the experimental design. Section 3 describes data and officer engagement with PayDash. Section 4 presents PayDash impacts on MGNREGS outcomes, Section 5 evaluates mechanisms, and Section 6 conducts benefit-cost analysis. Section 7 concludes.

2 Context and Experimental Design

MGNREGS provides rural Indian households paid work on infrastructure projects, implemented by a district-based bureaucracy composed of district, subdistrict (block), and local (Gram Panchayat, or GP) officials (summarized in Appendix Figure A1). We describe MGN-

[5]Relatedly, Deserranno et al. (2024) vary financial incentives across levels of a public health organization, and Saavedra (2024) shares information about illegal activities with local and/or higher-level officials. It aligns with research suggesting that greater autonomy can outperform stronger performance incentives in improving bureaucratic performance (Rasul and Rogger 2018; Bandiera et al. 2021; Rasul et al. 2021). 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.

REGS administration and how information acquisition costs constrain program implementation. We next present a conceptual framework to assess how lowering these costs affects MGNREGS efficacy and describe how the intervention tried to minimize them.

2.1 MGNREGS implementation

A. Administrative structure

GP officials collaborate with the primary subdistrict MGNREGS official - the program officer (PO) - to choose and implement public works (Gulzar and Pasquale 2017). The number of active MGNREGS worksites varies seasonally, counter-cyclical to agricultural activity (Imbert and Papp 2015). A GP agent, the Gram Rozgar Sevak (GRS), records worker details in an attendance register (muster roll) at the end of each six-day project workspell. Once an engineer verifies the associated work, the GRS logs attendance register and worksite information into the digital MGNREGS Management Information System (MIS) for subdistrict officers' approval. After evaluating the logged information, the subdistrict PO approves worker payments and digitally authorizes funds transfer orders. This completes "Stage I" of payment processing. At the subdistrict level, the PO reports to a Chief Executive Officer (CEO).[6]

District-level MGNREGS officer structure parallels the subdistrict level: the district PO oversees MGNREGS and reports to the district CEO.[7] District officers, however, have a purely supervisory role. Subdistrict and district officers can monitor work verification and payment processing via an MGNREGS website.[8] The website landing page displays state-wise attendance register delays at each of five phases of Stage I processing, using MIS data. From there, officers navigate through pages with step-specific delayed register counts for districts, subdistricts and GPs. Once at the list of GPs within a subdistrict, officers can click on GP-by-step links to view details for specific attendance registers. Officers discuss these statistics in person and via video conference and WhatsApp. Baseline surveys, described in Section 3.1, reveal that district officials use these data to decide performance incentives for subdistrict officers, with transfers a leading costly measure —77% of district CEOs transferred subordinates for performance reasons in the previous year.[9]

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

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

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

[9]Other measures include "show cause" notices that formally require explanation of poor performance or

"Stage II" of payment processing is largely automated. Once worker funds transfer orders are submitted by a subdistrict, the federal government's electronic funds management system routes payment requests to banks that deposit funds into workers' accounts. If a payment transfer fails (typically due to incorrect identification details), a rejected request is flagged for the subdistrict office to correct and re-route to the bank.

B. Implementation challenges

Payment delays and insufficient work provision are two critical and interlinked MGNREGS implementation issues. The mandate that Stage I worker payment processing be completed within eight days of a workspell is routinely violated. In the year before PayDash rollout, monthly wage processing time in our study states averaged 18 days, with 85% of subdistrict-month averages exceeding the eight-day threshold (Appendix Figure A2).[10] These delays impact wage receipt by workers – in the year preceding the intervention, the correlation between subdistrict Stage I processing time and time for wages to reach workers was 0.82.[11] Similarly, while the MGNREGS Act stipulates that households can receive 100 days of work annually, worker demand typically exceeds available jobs (Desai et al. 2015; Zimmermann 2021; Azim Premji University 2022).

At baseline, subdistrict administrators rated 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 officers' second highest implementation challenge (Figure 1b). When asked to rank subdistrict performance metrics, district POs identified work provision as most important, followed by worker payment delays (Figure 1c).

Administrative data suggest that Stage I payment processing delays are caused by a combination of delayed engineer visits to measure worksite progress, slow MIS data entry by GP agents, and subdistrict officer delays in validating documentation and signing off on payment requests. Managerial bandwidth limits contribute to these delays and to under-provision of work: Under-resourcing and heavy workloads weaken subdistrict officers ability to monitor and coordinate local officials (Dasgupta and Kapur 2020). Officer reports in baseline surveys

misconduct, suspensions, and salary withholding.

[10] The year before our intervention, India's Supreme Court deemed delayed MGNREGS worker wage payments nationwide "a clear constitutional breach committed by the State" (Supreme Court of India 2016).

[11] Appendix XX discusses analysis-relevant features of the available data on overall payment delivery time.

that they typically work over 70 hours per week, have 40 work-related calls per day and 44% report having an additional charge (see Appdendix Table A1). In our subsequent analysis, we summarize this by a workload index.

Heavy workload are compounded by poor IT infrastructure. Subdistrict officers rank "infrastructural issues such as poor internet connectivity and power shortages" as their top implementation challenge (Figure 1b). In semi-structured interviews, officers said these issues made using MGNREGS website data to monitor attendance registration processing time-consuming: An officer has to navigate hundreds of separate web pages to review performance for all locations under her purview.[12] Exporting and reformatting this information to meet officers' needs (e.g., comparing performance across subordinates or over time) requires additional effort, and web-connectivity problems further delay payment processing.

Rent extraction by officers may additionally worsen MGNREGS implementation by detracting from official duties or directly impacting program performance (e.g., officers may delay payment processing as a bargaining tactic). Officials minimized the importance of corruption in affecting MGNREGS implementation(Figure 1) but this could reflect self-serving biases: In over 4,800 external audits conducted in our study's control areas between October 2017 and March 2020, financial misappropriation was detected in 10% percent of GPs. Other research also highlights rent extraction by local and subdistrict officials (Niehaus and Sukhtankar 2013; Gulzar and Pasquale 2017). Frontline workers can directly seek bribes from jobseekers or collude with villagers to list them as workers without requiring work (and take a share of wages as payment), while subdistrict officers can use their sign-off powers to extract rents from frontline workers and, thereby, collude in corruption. Consistent with concentration of rent extraction at lower levels, the control-area audits were much more likely to identify concerns involving officials at the GP (13%) and subdistrict (2%), as compared to district (<0.01%), levels. Financial misappropriation was involved in officer-related GP and subdistrict level issues in 21% and 40% of cases, respectively.

In such a setting, the returns to technology-based solutions that ease bureaucrats' access to implementation data depend on the relative importance of effort costs vs agency concerns. Below, we describe PayDash, the technological innovation we evaluate, and provide a simple framework to identify how its impacts on program performance vary with officer incentives

[12] Subdistrict officials manage more than 45 GPs on average. Stage I is officially divided into five steps, suggesting an officer would review 225 landing pages to gather relevant information under her jurisdiction.

and the administrative level at which it is provided.

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 to officers' of accessing and sharing MGNREGS payment processing information. It relies on automatic timestamps generated as officers use the MGNREGS MIS to complete work verification and payment processing steps for each attendance register, eliminating user-provided data accuracy concerns (Muralidharan et al. 2021). Officers log in to access daily-updated information for their jurisdiction. The PayDash mobile app is offline compatible, allowing officers 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 app 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 GP 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 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, PayDash's performance dashboard displays charts of subdistrict and GP-wise historical processing times, both step-specific and overall.

The district version of PayDash is analogously 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 officials. 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 is managed by a principal P (district officer) and a manager M (subdistrict officer). 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:

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

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 potentially greater work provision.

The principal chooses between two incentive contracts: $I \in \{L, H\}$. A general way of modelling 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, however, the principal influences incentives not through wages but by transferring 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:

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

The principal's maximization problem under contract L is:

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

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 principal chooses contract H and the manager sets $e_M=0$. The impacts of introducing PayDash are as follows.[13]

1. *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.*

[13]The exact conditions for c_M and c_P are provided in Appendix B.

2. *In the presence of managerial rent seeking, however, providing PayDash to the principal is necessary to improve implementation.*

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

The intuition for these results is as follows. Absent managerial rent seeking, a reduction from PayDash in c_P alone causes the principal to switch from H to L contract and the manager to exert greater effort.[14] 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 the cost reductions, but manager effort increases regardless. With a shift to high manager effort, expected transfers drop by less under contract H as compared to L because low output still occurs with non-zero probability. In the case of a rent-seeking manager, simply providing the manager PayDash will not cause her to increase her effort since she directly benefits from $e_m = 0$. In contrast, as long as the manager's rent-seeking returns are not too high, providing the principal PayDash will lead her to choose contract L and the manager to exert high effort, improving implementation. We now describe the experimental design.

2.4 PayDash: Experimental Design

In the two North Indian states of Madhya Pradesh and Jharkhand, we randomly assigned the 73 districts and 561 subdistricts to one of four groups: 17 districts where district officials received PayDash ("District Only"), 16 where subdistrict officials received Paydash ("Subdistrict Only"), 20 where both district and subdistrict officials received PayDash ("Combination"), and 20 without Paydash ("Control").[15] 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 period ended in August 2018, to avoid potential officer deputations and transfers amid government preparations for the November 2018 Madhya Pradesh elections.

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

[15] Our sample includes all except a pilot district per state. Within each state, randomization was stratified by average attendance-register-by-worker payment time and average subdistrict volume of person-days worked from April 2015 to June 2016. Appendix Section C.1 provides details on variable construction. Treatments were assigned in roughly equal proportion across 50 Madhya Pradesh districts, and across 23 Jharkhand districts: one-third each to Control and Combination and one-sixth each to District Only and Subdistrict Only.

As part of rollout, we conducted 177 district-based, half-day sessions to administer baseline surveys and conduct training. Control and treatment officials were assigned to different sessions, as were subdistrict and district officials. All officials, 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 officials lasted an additional hour, during which they installed the PayDash mobile-phone app and were instructed how to use the platform.[16] Conditional on training session attendance, over 99% of officers completed a baseline survey.[17] Individual training was provided to officers who missed the initial sessions. We contacted each district at multiple points during the intervention to identify position changes and adjust PayDash access.[18] New officers in treatment areas were trained and provided PayDash. Officers transferred between treated areas had PayDash region-specific access updated, while those exiting treated areas had their login deactivated.

3 Data and Paydash Usage

We describe our data sources, check that our experimental sample is well-balanced, and conclude by describing PayDash usage patterns.

3.1 Data sources

PayDash usage data: Google Analytics data provides usage measures: session counts, usage duration, and WhatsApp messages and calls placed from PayDash.[19]

MGNREGS administrative data: We use data from the 17.5 million GP attendance registers issued in Jharkhand and Madhya Pradesh from September 2016 to August 2018. For each attendance register, we use the workspell start and end dates and subdistrict office payment request submission date to determine the duration of Stage I work verification and payment

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

[17] 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 do not differ with treatment status.

[18] After 1, 6, 13, and 17 months in Madhya Pradesh; 1, 6, and 10 months in Jharkhand, given its later rollout.

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

processing. We then calculate subdistrict-month processing time measures and number of attendance registers. Using additional administrative data, we construct subdistrict-month-level measures of work undertaken by MGNREGS participants, active worksites, and share of payment requests rejected at the bank routing stage.[20] 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 auditors external to communities.[21] Approximately 70% of our sample GPs experienced an audit covering some range of the intervention period, with coverage balanced across treatment arms.

Officer survey and transfer data: Baseline officer 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, providing additional information on MGNREGS administration and treated officials' use and perceptions of PayDash.[22] We gathered data from district offices on officers' postings and transfers through multiple rounds of phone-based transfer tracking.

3.2 Summary statistics and balance

Panel A of Appendix Table A1 shows that the average sample district has a population of 1.4 million, with 77% in rural areas, and consists of 7.7 subdistricts. The average subdistrict has 47 GPs, with significant variation. In the year prior to the intervention launch, more than 300,000 person days were worked across 5,500 attendance registers in the average subdistrict, and the subdistrict-level average register processing time for worker payments is 17.7 days.

Panels B and C report baseline characteristics of MGNREGS district and subdistrict officers, respectively. Officers are typically mid-career (aged early 40s), male and educated beyond the college level. Smartphone ownership is nearly universal (not shown) and more than 93% of officers reported interacting with the MGNREGS MIS as part of their duties at least once a day. High workloads are pervasive, with officers reporting working over 70 hours per week on average. 44% of district officers and 30% of subdistrict officers report an "additional charge" (tem-

[20] Worksites data for Jharkhand is available from April 2017 onward.

[21] Audits are assigned to GPs on a rotating basis and conducted over the course of approximately one week in a given GP. Appendix C.3 provides more information on social audit procedures.

[22] Our response rate is 77.1% and survey completion rate does not differ significantly by treatment.

porarily covering a vacancy in another position). Likely reflecting high workload, subdistrict officials report not being in regular (weekly) contact with frontline agents in 63% of GPs under their purview. Alongside, officers have limited knowledge of program outcomes: For instance, the knowledge gap related to payment delivery times, measured as proportional absolute deviation between the actual and perceived value of average time to payment in their jurisdiction over the last year, was 38% for district officers and 45% for subdistrict officials. Frequent subdistrict officer transfers, as mentioned in Section 2.1, also likely contribute to these knowledge gaps.

Our sample is well-balanced across treatment arms (Appendix Tables A1 and A2).[23] Throughout, our analysis follows our pre-registered analysis plan (PAP).[24] Appendix Table A3 lists and explains all plan deviations and extensions.

3.3 PayDash usage

Table 1 reports position-month-level PayDash usage statistics. We observe similar use by district and subdistrict officials, with 4-5 sessions and 25-30 minutes of mobile-based interaction total at each level (columns (1) through (4)).[25] Nearly all PayDash engagement within each level is by POs, who are solely tasked with MGNREGS management, rather than CEOs, who have a wider range of responsibilities. Figure 2 shows these usage patterns are stable over time. Columns (5) and (6) report the number of calls and WhatsApp messages sent using the in-app contact feature. Districts use this functionality more than subdistricts, possibly due to a greater share of supervision and communication with lower-level officials taking place remotely. Less than 5% of PayDash sessions for each officer type occur through the web-based interface (not shown), suggesting that officials value the mobile-tailored presentation and offline availability of app data.

Table 1 additionally reports the estimated coefficient on an indicator for PayDash access at both officer levels. These are based on regressions which also include month and strata fixed effects, where the sample is the set of locality-months in which officers at a given level

[23]Of 177 pairwise differences considered across 59 variables, one is significant below the 1% level, seven below the 5% level, and 24 below the 10% level. Out of 59 joint tests, the null is rejected twice below the 5% level and four times below the 10% level.

[24]https://www.socialscienceregistry.org/trials/1292

[25]Our measures are lower bounds since they do not capture mobile-based use in offline mode and officers when transferred generate monthly zeros until their change in status is tracked and PayDash access updated. Appendix Table A5 shows that districts and subdistricts average roughly 12 sessions and 70 minutes of mobile-based engagement per month, primarily among POs, when we condition on positive usage.

received PayDash. Panel A shows no differences in usage for subdistrict POs when district officers also have access. Differences are larger, though noisily estimated, for district POs in Panel B, suggesting they use PayDash less when their subordinates have platform access.

Finally, a brief platform shock allows us to shed light on the value of real-time information for officials. A central government server outage shut down PayDash's attendance register API for much of July 2017, 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 (Paydash rollout in Jharkhand occurred after the outage). In odd columns, we regress locality-month measures of officer 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 officials placing value on the real-time information provided by PayDash, subdistrict and district PayDash usage halved during the data outage, but subsequently recovered.

4 Did PayDash Impact MGNREGS Performance?

We describe our empirical approach followed by PayDash impacts on MGNREGS outcomes.

4.1 Empirical approach

Our PAP for MGNREGS administrative data-based analysis provided a panel data specification, where we include pre-intervention data to potentially improve precision of estimated impacts. Specifically, for analyzing treatment effects on outcome Y_{sdt} for subdistrict s in district d using monthly panel data, we estimate:

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

α_{sd} and α_t are subdistrict and month fixed effects. We first examine impacts of PayDash access at any officer level in Section 4.2, and for that case T_{dt} is the pooled treatment provision ("Any PayDash") indicator. We include district-specific controls, X_{dt}, for quarter of year to improve precision given region-specific seasonal variation in MGNREGS activity and for linear time trends to adjust for any chance differential pre-trends. Standard errors are clustered by district throughout. The analysis sample range spans September 2016 to August 2018, with the intervention lasting from February 2017 through August 2018.

Our OLS estimates can be interpreted as intent-to-treat effects in a setting which was marked by interruptions in PayDash availability (these include the temporary data outage discussed in Section 3.3 and position-specific interruptions due to lags between officer movement and updating of PayDash access following transfers tracking rounds). For subsequent analysis of outcomes for which we only collected a post-treatment measure, we regress the outcome of interest on a treatment indicator and randomization strata fixed effects. We describe data-set-specific adjustments to this approach subsequently in the text when relevant.

In order to ensure social protection for rural households when agricultural work opportunities are limited, MGNREGS work provision is concentrated in the four pre-monsoon late spring and summer months when agricultural activity is limited. We examine how treatment impacts vary with seasonality in agricultural activity, adding an MGNREGS high-season indicator and its interaction with the PayDash indicator to Equation (1).[26]

To examine 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 τ months relative to the provision of PayDash, where $\tau = -5$ captures all periods five or more months prior and $\tau = 8$ all periods eight or more months after.

Given the availability of administrative panel data, our PAP registered the use of generalized difference-in-differences (two-way fixed-effects) estimators. Within each state, we randomized treatment status .. However, with potential heterogeneity in treatment effects over time and the staggered rollout of PayDash within and across states, a recent literature (see, e.g., de Chaisemartin and D'Haultfoeuille (2023) for a survey) highlights concerns of potential bias in treatment effect estimates based on approaches of the type in Equations (1) and (2). Appendix Table A4 therefore demonstrates general robustness to using alternative heterogeneity-robust estimators (Callaway and Sant'Anna 2021; Sun and Abraham 2021; Borusyak, Jaravel, and Spiess 2024; de Chaisemartin and D'Haultfoeuille 2024), as well as to excluding controls and restricting to post-rollout observations.

[26]The high season is defined as April-July in Jharkhand and May-August in Madhya Pradesh, during which the average monthly volume of MGNREGS days worked in control areas is 78% higher than in other months over the evaluation period. The state-specific ranges reflect differences in MGNREGS participation observed in administrative data.

In Sections 5.1 and 5.3, we consider the relative effects of the different treatment arms, replacing the pooled treatment indicator in Equation (1) with indicators for provision of District Only PayDash (TD_{dt}), Subdistrict Only PayDash (TS_{dt}), and Combination PayDash (TC_{dt}):

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

This specification allows us to compare the impacts of district- and subdistrict-level PayDash provision, and test for substitutability (against $H_0 : \beta_3 = \beta_1 + \beta_2$). When analyzing seasonal heterogeneity and cross-sectional measures separately by treatment arm, we analogously replace the pooled treatment indicator with treatment arm indicators in corresponding specifications. In Section 5.2 we examine the relevance of officers' administrative environment to the effects of PayDash, supplementing Equation (1) with interactions of treatment provision and time-invariant measures of administrative structure and officer workload.

4.2 PayDash Impacts

Panel A of Figure 3 reports the event-study plot for payment processing time. Small declines in payment processing time begin the first month after PayDash is provided, strengthen over time and then stabilize roughly five months after PayDash provision. In Figure 4 we plot estimates from regressions of the form described in Equation (1) where outcome variables are different time-ranges for Stage I processing. The left-most bin shows a sharp 12 percentage point (25%) rise in the probability that payment processing was not "late", i.e., beyond the eight-day maximum mandated by regulation. In both cases, the dynamics are similar using the Sun and Abraham (2021) estimator (Appendix Figure A6). The pattern also holds up when we examine impacts separately by treatment arms (Appendix Figure A5). More generally, PayDash caused a leftward shift in the processing time distribution, with significant declines in the shares of attendance registers processed within longer time ranges, including beyond 32 days.

In Table 3 we first examine PayDash impacts on worker payment processing. Panel A presents average impacts while Panel B investigates seasonality of treatment effects. PayDash provision reduced processing time by 24% (27.4 log points; column 1).[27] Consequently, the share of payments that were "late", i.e., took more than eight days to process, also fell (column 2). Improved payment processing speeds were accompanied by reduced variability, measured

[27]The relationship holds when weighting the subdistrict-month-level observations by number of attendance registers (Appendix Table A6) and considering processing times in levels (Appendix Table A7).

as the average absolute deviation of wage processing time from the subdistrict-month median, of 1.2 days (18%; column 3). Finally, we consider the likelihood of worker payment requests being rejected after Stage I processing, measured as payment rejection rates across wagelists (groupings of attendance registers for which payment requests are jointly submitted). Rejections often reflect officials entering invalid recipient bank or individual identifying information into the MGNREGS system.[28] If PayDash caused officials to reduce processing time at the expense of work quality, rejection rates could rise. Column (4) shows PayDash did not increase rejection rates. Another concern is that officers' processed fewer attendance registers (possibly by extending workspell length), reducing worker payment cycles. Appendix Table A7 shows PayDash did not impact the number of registers processed or workspell length. Panel B shows that improvements in PayDash's processing occurred throughout the year.

Next, we consider MGNREGS work outcomes. The Panel B, Figure 3 event study shows household MGNREGS participation increased after PayDash was implemented. Similar to payment processing, the increase in work participation – which could reflect some combination of increased worker demand in response to improved program implementation (e.g., faster payment processing) and reduced rationing as officers provide more worksites – begins immediately after PayDash is implemented and stabilizes at a higher level approximately five months later. Columns (5)-(8) of Table 3 report treatment effects for an array of MGNREGS participation outcomes using regressions of the form reported in Equation (1). As before, Panel A reports average impacts while Panel B considers seasonality. Access to Paydash resulted in a 9% increase in monthly person-days of work per participating household with improvements generalized over the year (column 5). In contrast, comparing across Panels A and B for total working households in column (6), PayDash impacts vary across seasons with relatively higher number of working households in high season. The same seasonal pattern holds for total person days worked where in high season we see a significant 17% increase in work days (column 6). Considering worker composition in Appendix Table A7, we see that PayDash increased the average share of below poverty line participants by 0.6 percentage points (3%), with no impact on relative female participation.

How were extensive margin changes in household working achieved? In column (8) our outcome of interest is the monthly number of active worksites. In control areas, this value

[28]Following payment rejections, a subdistrict office can attempt to address the source problems and re-submit payment requests. Gathering necessary information requires coordination with local officials, potentially leading to additional delays.

increases from an average of 291 in low season to 397 in high season. When comparing across panels, we see that PayDash caused a 24% increase in active worksites *only* in high season, when worksite availability is more likely to be a binding constraint. The timing of worksite expansion points to it being an important mechanism underlying the PayDash-induced increase in new households working for MGNREGS.

We now turn to evaluating how PayDash influenced the behavior of district and subdistrict officials responsible for MGNREGS implementation.

5 How did PayDash enhance performance?

We use experimental variation in which level of the bureaucracy receives PayDash to assess substitutability. Next, we use quasi-experimental variation in district administrative structure to investigate PayDash impacts on officers' workload. Following this, we evaluate how PayDash affected officer transfers, program malfeasance, and worker demand. We conclude by examining impacts on officer MGNREGS knowledge.

5.1 Substitutability in PayDash provision

Random variation in the level of the bureaucratic hierarchy receiving PayDash allows us to examine substitutability in PayDash provision to district and subdistrict officers. In Table 4 we examine the same set of outcomes as Table 3, but now report results from regressions of the form described by Equation (3), where impacts are considered separately by treatment arm. Panel A estimates average impacts by treatment arm while Panel B examines differences in impacts across high and low season. At the bottom of each column, 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 with the impact of simultaneously 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.

Overall, the Table 4 results show that PayDash improved processing times and household participation intensity, irrespective of level offered. For processing time outcomes, as before, impacts are similar across high and low season. In Panel A we see that, demonstrating impact substitutability at the district and subdistrict levels, the effect of providing PayDash to both district and subdistrict officers is significantly smaller than the sum of the district-only and subdistrict-only effects for log processing time ($p = 0.032$) and log person-days per working household ($p < 0.001$).[29] Overall, we can reject the hypothesis that PayDash had a greater impact on processing time outcomes when provided to both district and subdistrict officers as opposed to either level alone (columns 1-4). Columns (5)-(8) consider work outcomes. As before, we see strong seasonal impacts. In Panel B we see that, other than for days of employment for working households, we cannot reject impact substitutability across treatment arms.

Viewed through the lens of our conceptual framework, these results imply that the gains from PayDash were not solely due to better district-level monitoring of rent-seeking subdistrict officers. In that case, performance benefits would only accrue if district officers have Paydash access. The substitutability of district- and subdistrict-level PayDash is consistent with subdistrict information constraints impeding program implementation – and PayDash for district officials leading to improvements through some combination of sharing information with subdistrict subordinates (thereby reducing effort costs of information collection for subdistrict officials) and better incentivizing effort by subdistrict officers (potentially, by increased conditioning of performance incentives on managerial effort). We now provide additional evidence that supports this interpretation.

5.2 Heterogeneity by officer workload

If PayDash improves MGNREGS outcomes by facilitating information acquisition by subdistrict officers, then effects should be larger for officials with heavier workloads.[30] Following Independence, India's subdistricts were established as the geographic unit for implementing rural development programs. Since their rollout was completed in 1964, subdistrict boundaries have remained unchanged despite differing population growth. In contrast, GPs were created by a 1993 constitutional change and states set minimum and maximum population thresholds for GPs and readjust GP boundaries within subdistricts following new census data (Narasimhan and Weaver 2024). [31]

Constant subdistrict borders combined with population-based GP definition has meant

[29]For the share processed within 8 days and average absolute deviation outcomes, $p = 0.014$ and 0.116, respectively.

[30]In addition to administrative environment, our analysis plan indicated examining heterogeneity by officer personality and cognitive characteristics. Appendix Table A11 presents these results.

[31]In Madhya Pradesh the minimum GP population size is 1,000 (with no explicit maximum) while in Jharkhand GPs should have a population of approximately 5,000. No boundary changes for either type of administrative unit occurred during our evaluation period.

significant variation in the number of GPs across subdistricts. On average, subdistrict officials in above-median districts in terms of GPs per subdistrict ("high-GP-ratio") oversee 80 GPs, as compared to 32 in below-median ("low-GP-ratio") districts. Appendix Table A13 shows a positive relationship for subdistrict officers between being based in a high-GP-ratio district and a workload index composed of baseline measures of weekly hours worked, calls per work day, additional charge, and irregular local agent contact.[32] In contrast, we see no evidence of increased workload for district officers when they oversee more subdistricts, potentially reflecting the smaller range of values in this dimension.

Control high-GP-ratio districts took 16.4 days to process payments, compared to 11.6 days for low-GP-ratio districts. Column (1) of Table 5 shows that PayDash reduces average processing times by 30% (36.1 log points) in high-GP-ratio districts, more than 1.5 times the magnitude of the improvement in low-GP-ratio districts. Column (2) shows that the concentration of PayDash impacts in high-GP-ratio districts is robust to the inclusion of a host of interacted controls.[33]

We next allow PayDash impacts to vary directly by whether a district is above-median in terms of average subdistrict PO workload ("high workload"). Column (3) of Table 5 shows a concentration of payment processing improvements in high-workload areas. In column (4), where we further include a high-GP-ratio interaction and interacted controls, heterogeneity in PayDash impact with workload remains undiminished relative to column (3). The high-GP-ratio interaction, however, is statistically insignificant and slightly more than half the magnitude of the estimate in column (2), consistent with officer workload underlying much of the heterogeneity in PayDash impact by administrative structure.[34] Columns (5) through (7) show that improvements in the other processing time outcomes and household MGRNEGS participation intensity are also stronger in high-workload areas. Finally, we observe in Appendix Table A15 that subdistrict POs use PayDash more in high-workload districts, consistent with a greater value of reducing information acquisition costs for this group.

In Appendix Table A16,..

[32]The index is the average of z-scores calculated for each component. Appendix Table A13 further shows a positive linear relationship with GPs per subdistrict.

[33]In particular: log population, rural population share, above-median total subdistricts, state, and baseline district PO and average subdistrict PO post-graduate education completion and daily MIS usage.

[34]Results are robust to using within-state and continuous measures of administrative structure and workload in Appendix Table A14.

5.3 Impacts on officer behavior and knowledge

A. Posting transfers

Our conceptual framework demonstrates how, in settings where acquiring information on manager effort is costly, principals may judge performance based on more readily observable program outcomes that are noisy measures of effort. If PayDash lowers the cost of information acquisition, the principal will switch to performance incentives that condition more heavily on managerial effort. This, in turn, increases the returns to the manager from increasing effort. In our study context, bureaucratic posting choice is a commonly used performance incentive; 45% of subdistrict officers in control districts having been transferred within six months of intervention rollout in each state.[35]

Column (1) of Table 6, based on data collected via calling rounds to district offices, shows that District-level PayDash reduced the probability of subdistrict officer transfer within six months by 10.6 percentage points (24%), similar in magnitude to and statistically indistinguishable from the effect when both district and subdistrict levels receive PayDash ($p = 0.505$). In contrast, the impact of only subdistrict officials having platform access is positively signed and statistically distinguishable from those of the District Only and Combination PayDash treatments ($p = 0.012$ and 0.060, respectively). Consistent with the idea that transfers are determined at the district level, we cannot reject equality of the sum of district and subdistrict PayDash from the impact of providing to both. Extending the range of consideration to 17 months – the maximum length available, for Madhya Pradesh alone due to its earlier PayDash rollout – we observe a similar pattern in Table A10, with PayDash reducing subdistrict transfers only when district officials are among those with platform access.

B. Malfeasance and citizen program demand

We create an 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

[35] Among control endline respondents, being transferred during the study window is associated with worse knowledge of local delays, a lower self-reported probability of being held responsible for a payment delay and higher self-reported probability of being rewarded for timely payment performance.

violations (reported in 19% of control locations).The audit irregularity index is not impacted by PayDash (column 2, Table 6). Appendix Table A9 shows no significant treatment effects on individual index components or the likelihood of GP, subdistrict, or district officials being named in connection to audit-detected issues.

Villager demand for MGNREGS work serves as a separate margin for judging officer performance. We construct a GP-level indicator for unmet worker demand using social audit reports on villagers' unmet work demand.[36] Column (3) shows a 12.4 percentage point higher probability of unmet demand in PayDash districts. Given higher worker participation in these districts, we interpret increased program demand as reflecting improved implementation (e.g., quicker payment processing), which increased workers' perceived value from participating and thus demand.

C. Officer knowledge

Finally, we analyze data from post-intervention surveys to examine PayDash's impact on subdistrict officers' program knowledge. We calculate the knowledge gap for subdistrict POs, which is defined as the proportional absolute deviation between the actual and perceived value of average time to payment in their subdistrict for the most recent fiscal year. Column (4) of Table 6 shows that PayDash reduced their average knowledge gap by 7.8 percentage points (19% of the control mean), with indistinguishable impacts across treatment arms.

Figure 5 shows more evidence supporting the information channel. Post-intervention surveys revealed that 81% of district officials and 60% of subdistrict officials who received PayDash found it easier to learn about MGNREGS worker payment processing in their jurisdictions. 19% and 27% of district and subdistrict officers, respectively, report that PayDash helped them acquire information.[37] PayDash prompted officers to prioritize payment processing, as reported by 31% of district officials and 46% of subdistrict officials. When asked about how they used PayDash information, 68% of district officers and 63% of subdistrict officials reported sharing it with their subordinates. 25% of district officials and 40% of subdistrict officer also reported using PayDash to evaluate subordinate performance.

[36]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". As each audit typically has an 11-month reference period, we are unable to consider seasonality in changes in work demand.

[37]94(75)% of district(subdistrict) POs answered affirmatively to either information-related question.

6 Cost-Benefit Analysis

PayDash improved payment processing speed and safety net access without adversely impacting quality or increasing rent-seeking. In Table 7 we provide a back-of-the envelope cost-benefit assessment of providing officers PayDash.

Panel A reports the estimated cost as consisting of platform development costs of approximately \$98,000 and annual maintenance costs of around \$36,000.

In Panel B, we estimate benefits to citizens from PayDash as consisting of two components. First, increased work days. Our estimates suggest that 390 additional person-days were worked per subdistrict-month as a result of PayDash. These additional workdays amount to nearly \$180,000 additional funds going directly to rural, poor households

Second, a reduction in 2.5 days to payment benefits citizens by shortening the time period during which they require a short-term subsistence loan to cover household consumption costs as they wait for wage payments. We calculate a household's gains as the benefits of not needing an additional three-day consumption loan. We utilize the average interest terms reported (20%, compounded daily) for a non-business loan among households in the bottom two consumption quintiles in the 2019 All-India Debt and Investment Survey. or more details, refer to the notes in Table 7 and Appendix C.5. This calculation shows that, for the approximately 1,200 households that worked in each subdistrict on an average month during the intervention period, this averted interest totals approximately \$908.

While relatively small on a per-household basis, these benefits total about \$4.5 million across the study area in a given year. The benefits to citizens outweigh the total development and maintenance costs for the first year of deployment alone (amounting to \$134,078) by a factor of 49. In subsequent years, when development costs are not incurred, the benefits outweigh the cost of the platform maintenance by 186 times. Our assumptions related to workdays and loan costs averted are aimed at being realistic, yet conservative; less favorable loan terms, such as those with higher interest or pre-payment penalties, will significantly increase these benefits.

7 Conclusion

Our field experiment, conducted at scale across two large Indian states, randomly assigned access to PayDash, a mobile- and web-based platform to officers responsible for MGNREGS implementation. PayDash access reduced payment processing times by 24% over the control mean, while improving other aspects of program benefits delivered, including work provision during the agricultural lean season, whether made available at the district and/or subdistrict level. This substitutability is due, at least in part, to district officers sharing information from PayDash with subordinates. Consistent with the hypothesis that reduced information acquisition costs allows principals to better target incentives and limit the usage of blunt incentives, we observe a 20 percent decline in transfers of subordinate officials across jurisdictions. Program performance gains in program were achieved without worsening work quality: We see no increases in the rate of worker payment rejections or local corruption as assessed through independent government audits.

Our results highlight how seemingly small costs of information acquisition for government officials who administer public programs can be an important constraint to service delivery in low-income settings. These improvements were achieved by reducing information access costs in an environment that was already largely digitized. Crucially, cost reductions were particularly important in locations where subdistrict officers reported higher workloads.

Since running the original PayDash study, several additional state governments have requested access to the tool, and the central government continues to support PayDash and is considering a broader national roll-out. Doing so promises to be remarkably cost effective: The annual cost of a one-day reduction in processing time was only \$0.10 per MGNREGS participating household in the study treatment locations, and benefits accruing to households were at least 49 times the cost of the platform in the first year alone.

The cost effectiveness of this initiative, and its clear lack of impact on work-related quality declines and corruption, point to how digital investments can have positive benefits on state capacity to deliver services to vulnerable citizens. More broadly, our findings highlight the potential of deploying add-on digital tools to deliver real-time information to busy bureaucrats tasked with safety net delivery in low-capacity settings.

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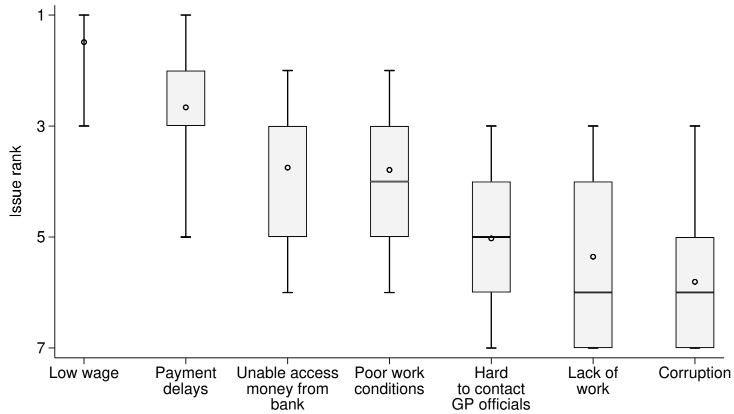
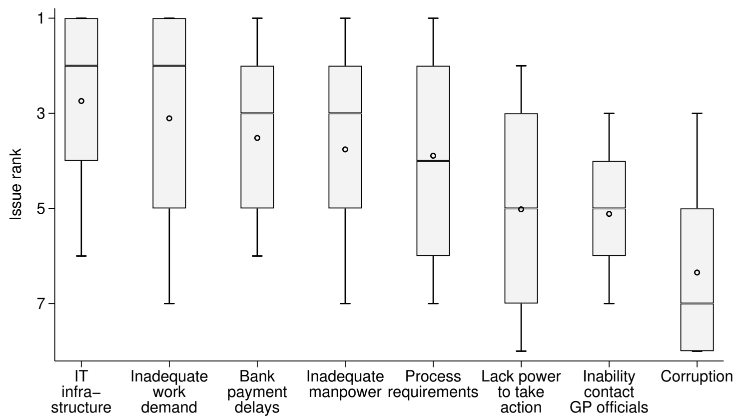
Figures and Tables

Figure 1: MGNREGS Environment for Subdistrict Officers

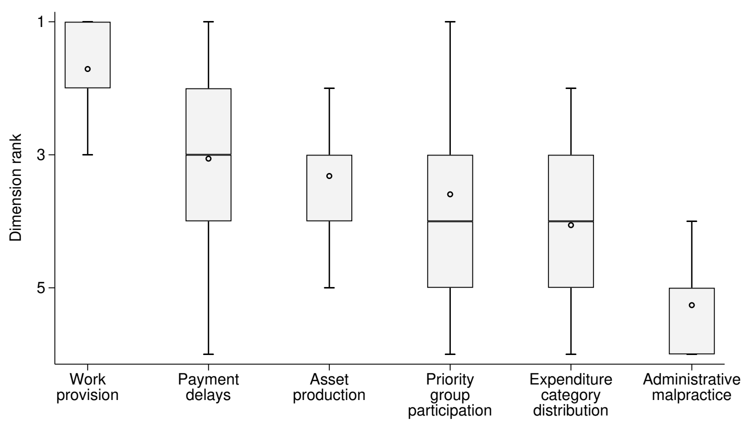
(a) MGNREGS worker challenges - subdistrict reported



(b) Implementation challenges - subdistrict reported

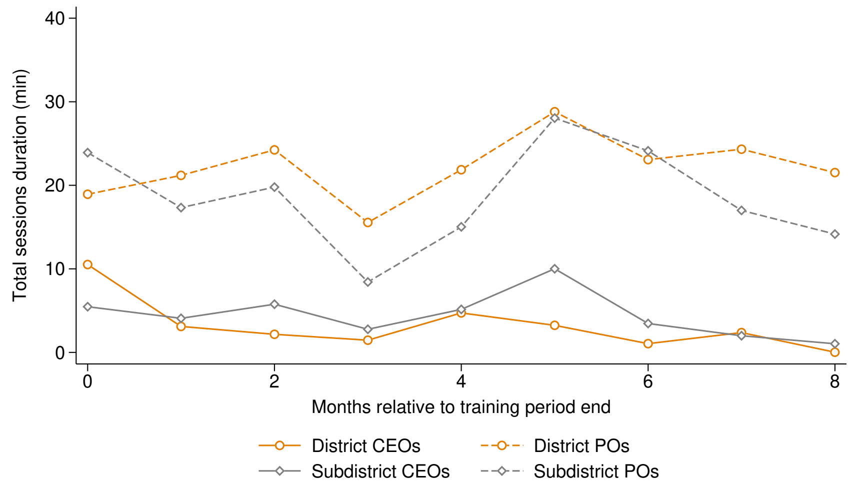


(c) Performance metrics - district reported



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 officials, based on baseline reports by District POs. Circles plot the mean, boxes show the median and interquartile range, and whiskers plot the 10th and 90th percentiles. Appendix Table C.4 provides detailed definitions for the categories in each panel.

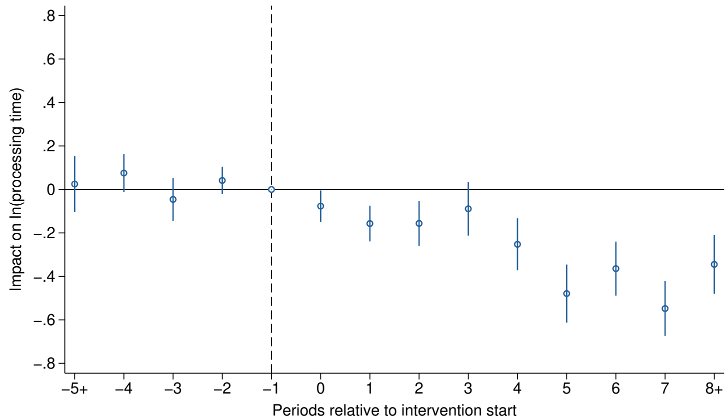
Figure 2: Officer PayDash Usage Over Time



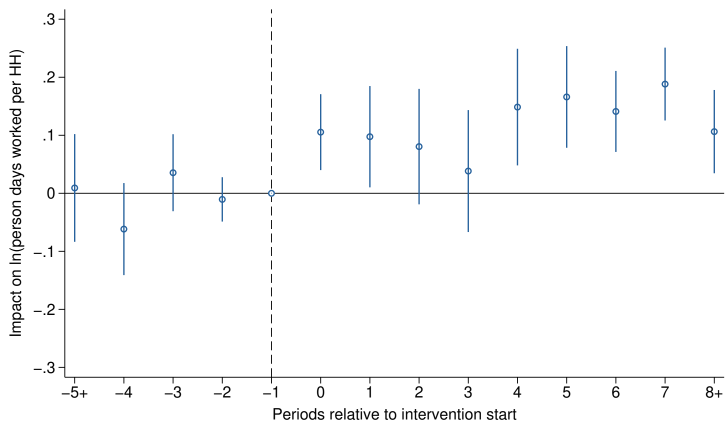
Notes: The figure shows monthly average PayDash usage duration for each of the four officer groups (district and subdistrict CEOs and POs) following the two-month period during which group and individual-follow-up PayDash training sessions occurred. The plotted range is the maximum available for both states.

Figure 3: Dynamics of PayDash Impacts

(a) Log processing time

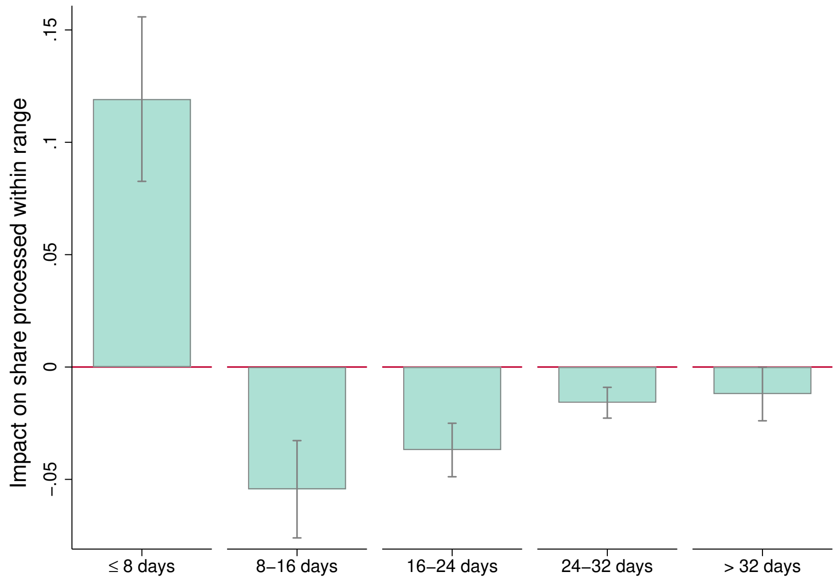


(b) Log days per working household



Notes: The figure shows event-study plots, constructed based on Equation (2) for the impacts of any PayDash provision, with outcomes of log average processing time (Panel A) and log person-days worked (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.

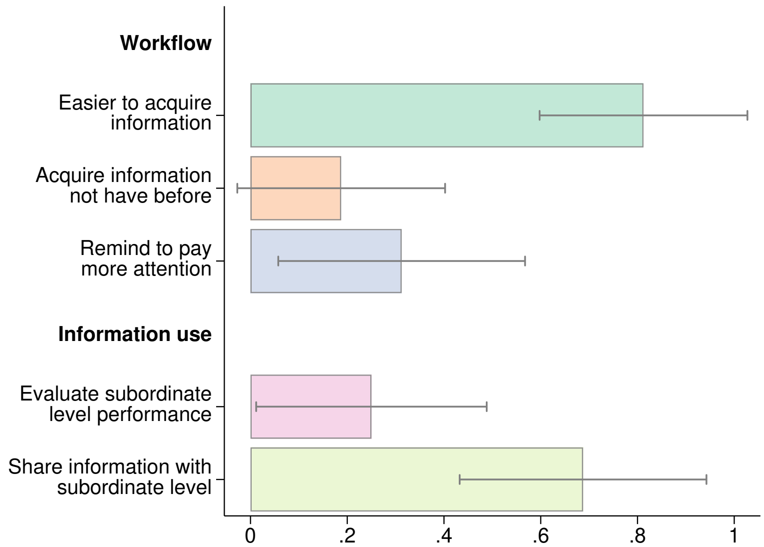
Figure 4: Effects on Processing Time Distribution



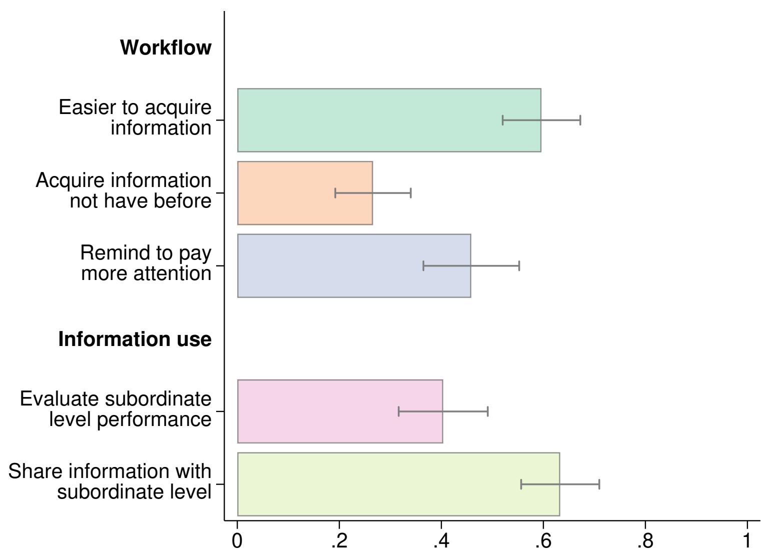
Notes: The figure shows estimates following Equation (1) for the impacts of any PayDash provision, with outcomes of the share of attendance registers processed within the time range specified in each column. Standard errors in the underlying subdistrict-month-level regressions are clustered at the district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

Figure 5: Mechanisms of Impact - Bureaucrat Self-Reports

(a) District Officials



(b) Subdistrict Officials



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: Officer 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 Officers						
District Only PayDash	4.39	0.43	26.61	1.48	17.17	0.12
	[9.42]	[1.98]	[71.38]	[8.46]	[68.76]	[1.30]
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: Columns in each panel report means and standard deviations of the 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)-numbered columns consider usage by program (chief executive) officers. Also shown are the coefficients on an indicator for PayDash provision at both administrative levels in regressions of the listed variables 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. Significant at *10 percent, **5 percent,***1 percent. "Sessions" includes both web and mobile usage, while "Duration" captures mobile usage only.

Table 2: Usage Impacts of Exogenous Shock to 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 Officers				
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-numbered columns) or indicators for pre- and post-outage months (even-numbered 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 3 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: Impacts on Worker Payment Processing and Program Scale

	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	-0.272***	-0.119***	-1.133***	-0.001	0.093***	-0.029	0.064	0.016
	(0.043)	(0.018)	(0.259)	(0.004)	(0.020)	(0.068)	(0.070)	(0.062)
Control mean	2.375	0.483	6.278	0.041	2.256	7.122	9.378	5.427
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	-0.023	0.001	-0.267	0.002	0.033	0.138***	0.172***	0.209***
	(0.036)	(0.016)	(0.173)	(0.004)	(0.022)	(0.044)	(0.043)	(0.051)
Any PayDash	-0.265***	-0.119***	-1.054***	-0.001	0.082***	-0.074	0.007	0.008
	(0.043)	(0.018)	(0.258)	(0.004)	(0.022)	(0.063)	(0.066)	(0.064)
Any + High×Any, p-value	0.000	0.000	0.000	0.705	0.000	0.470	0.041	0.025
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. Control means in Panel A calculated over pre-intervention period. 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	-0.259***	-0.107***	-1.247***	0.003	0.118***	0.006	0.124	0.011
	(0.068)	(0.028)	(0.441)	(0.006)	(0.028)	(0.091)	(0.109)	(0.089)
Subdistrict Only PayDash	-0.258***	-0.127***	-0.933**	0.008	0.110***	-0.036	0.073	0.097
	(0.062)	(0.026)	(0.374)	(0.008)	(0.030)	(0.061)	(0.066)	(0.107)
Combination PayDash	-0.295***	-0.125***	-1.174***	-0.011*	0.058**	-0.053	0.005	-0.038
	(0.063)	(0.027)	(0.395)	(0.006)	(0.029)	(0.103)	(0.099)	(0.078)
D = S = C, p-value	0.869	0.837	0.840	0.123	0.203	0.856	0.616	0.537
D + S = C, p-value	0.032	0.014	0.116	0.074	0.000	0.853	0.164	0.319
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	0.010	0.022	-0.270	0.003	0.005	0.183***	0.189***	0.236***
	(0.034)	(0.016)	(0.179)	(0.006)	(0.026)	(0.047)	(0.048)	(0.075)
× Subdistrict Only PayDash	-0.011	0.004	-0.197	-0.010	0.027	0.097	0.124**	0.193***
	(0.053)	(0.023)	(0.271)	(0.007)	(0.026)	(0.059)	(0.055)	(0.060)
× Combination PayDash	-0.059	-0.017	-0.316	0.011*	0.062**	0.131*	0.193***	0.196***
	(0.044)	(0.018)	(0.214)	(0.006)	(0.030)	(0.067)	(0.060)	(0.055)
District Only PayDash	-0.253***	-0.108***	-1.171**	0.003	0.109***	-0.040	0.070	0.004
	(0.068)	(0.029)	(0.447)	(0.006)	(0.030)	(0.086)	(0.104)	(0.090)
Subdistrict Only PayDash	-0.251***	-0.127***	-0.858**	0.009	0.099***	-0.078	0.020	0.089
	(0.062)	(0.026)	(0.370)	(0.008)	(0.032)	(0.058)	(0.063)	(0.109)
Combination PayDash	-0.282***	-0.121***	-1.086**	-0.011	0.042	-0.102	-0.059	-0.047
	(0.062)	(0.026)	(0.386)	(0.006)	(0.028)	(0.094)	(0.091)	(0.078)
High, total: D = S = C, p-value	0.563	0.389	0.793	0.802	0.883	0.601	0.697	0.658
High, total: D + S = C, p-value	0.182	0.188	0.138	0.730	0.014	0.420	0.135	0.078
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. They also present p-values from tests of the equality in the high season of impacts across treatment arms ("High, total: D = S = C", or (D+High×D) = (S+High×S) = C+High×C)) and of the sum District Only and Subdistrict Only PayDash impacts with the Combination PayDash impact ("High, total: D + S = C", or (D+High×D) + (S+High×S) = C+High×C)). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 5: Heterogeneity by Administrative Structure and Workload

	Log processing time				Share processed "late" (>8 days)	Absolute deviation (days)	Log days per working household
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Any PayDash							
× High GPs per subdistrict	-0.157**	-0.175*		-0.096	-0.039	-0.467	-0.068
	(0.077)	(0.094)		(0.094)	(0.041)	(0.654)	(0.041)
× High subdistrict workload			-0.178**	-0.263***	-0.109***	-1.481**	0.092**
			(0.079)	(0.087)	(0.039)	(0.584)	(0.035)
Any PayDash	-0.204***	0.789	-0.192***	1.023	0.224	10.851*	0.318
	(0.052)	(1.043)	(0.057)	(1.002)	(0.418)	(6.452)	(0.297)
Observations	12,629	12,629	12,629	12,629	12,629	12,629	12,629
Interacted controls		X		X	X	X	X
Control outcome mean, high	2.69	2.69	2.52	2.52	0.611	6.25	2.41
Control outcome mean, low	2.30	2.30	2.31	2.31	0.475	6.24	2.20

Notes: All columns report estimates following Equation (1) with additional terms included as described subsequently. Columns (1), (2), and (4) through (7) include an interaction of the treatment indicator with an indicator for being an above-median district in terms of average number of panchayats per subdistrict. Columns (3) through (7) include an interaction of the treatment indicator with an indicator for being an above-median district in terms of the average value of the baseline subdistrict PO workload index. Columns (2) and (4) through (7) additionally include interactions (not shown) of the treatment indicator with an indicator for being an above-median district in terms of number of subdistricts, a Jharkhand state indicator, district-level measures of rural population share and log population, baseline district PO post-graduate education completion and daily MIS usage, and the district-level baseline average post-graduate education completion and and daily MIS usage for subdistrict POs. Control means calculated over the pre-intervention period, with "high" and "low" corresponding respectively to above- and below-median districts in terms of average number of panchayats per subdistrict in columns (1) and (2) and in terms of average baseline subdistrict PO workload index in columns (3) through (7). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 6: Impacts on Audit, Knowledge, and Transfer Outcomes

	Officer posting transfer	Social audits: Issue irregularity index	Social audits: Community work demand	Program officer knowledge gap
	(1)	(2)	(3)	(4)
Panel A: Pooled Treatment				
Any PayDash	-0.057	-0.029	0.124**	-0.078*
	(0.044)	(0.056)	(0.061)	(0.042)
Control mean	0.447	0.000	0.297	0.418
Observations	1,122	20,621	20,621	176
Panel B: Treatment Arms				
District Only PayDash	-0.106**	0.004	0.088	-0.067
	(0.051)	(0.070)	(0.076)	(0.056)
Subdistrict Only PayDash	0.029	-0.030	0.102	-0.100**
	(0.055)	(0.056)	(0.076)	(0.048)
Combination PayDash	-0.073	-0.063	0.183**	-0.072
	(0.051)	(0.056)	(0.074)	(0.048)
D = S = C, p-value	0.036	0.289	0.435	0.780
D + S = C, p-value	0.955	0.621	0.944	0.192
Observations	1,122	20,621	20,621	176

Notes: In Panel A, column (1) reports estimates from regressions at the subdistrict PO level of the listed variable on treatment arm indicators and strata fixed effects. Columns (2) and (3) report estimates from regressions at the audit level of the listed variable on treatment arm indicators and strata fixed effects. Column (4) reports estimates from regressions at the subdistrict-position level of the listed variable on treatment arm indicators as well as strata fixed effects and a PO indicator. For each column, 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"). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

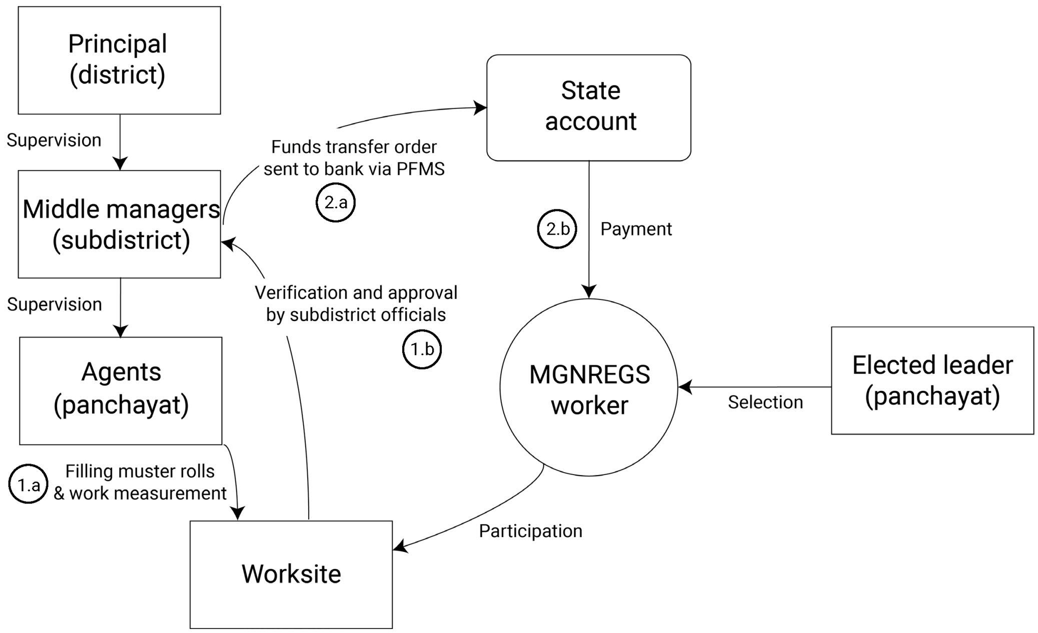
Table 7: Benefit-Cost Analysis

Category	Amount	Units	Source
Panel A: PayDash Costs			
Initial development	\$98,420	Fixed development	Authors' estimates
Annual development maintenance	\$25,074	\$/year	Authors' estimates
Annual development oversight	\$10,584	\$/year	Authors' estimates
Panel B: Direct Benefits			
Reduced time to payment	-2.072	Days per subdistrict*month*.8 (estimated pass-through to worker final payment receipt)	Table 3
Additional days worked	390	Person-days worked per subdistrict*month	Table 3
Value of additional workdays paid	\$179,692		Authors' calculations
Panel C: Indirect Benefits			
Number hhs avoided short-term loans	1,212	Number hhs worked per subdistrict-month	Control value in intervention period (Table A7)
Principal loan cost averted	\$7.15	Anticipated cost of hh consumption for 3 days based on state average rural hh size and RBI poverty threshold	Authors' calculations
Interest averted	\$0.75	Interest per household*month; assume 20% interest rate with no pre-payment fee for a month-long loan, compounded daily; assume all loans repaid in two weeks	All India Debt and Investment Survey 2019 - mean common loan terms reported by Jharkhand and Madhya Pradesh-based respondents taking loans for non-business purposes
Total interest averted	\$908	Per subdistrict*month	Authors' calculations
Panel D: Scaled Estimates			
Total Costs	\$134,078	Annual cost for year 1	Authors' calculations
Direct Benefits: Additional wages paid	\$2,156,306	Increased direct benefits paid (annual)	Authors' calculations
Indirect Benefits: Interest Averted	\$4,477,387	Interest averted (annual)	Authors' calculations
Panel E: Benefit-Cost Ratio			
Year 1	49.5:1	Total direct + indirect benefits: Total cost	Authors' calculations
Future years	186.0:1	As above, but excluding development cost	Authors' calculations

Notes: INR to USD exchange rate of 0.01537, as of April 1, 2018, taken from oanda.com. Average rural household sizes for 2017-18 drawn from PLFS data as reported by MOSPI. Per capita poverty lines taken from RBI data for 2012 and inflated to 2019 levels using PBI-reported rural CPI inflator. MGNREGS wage rate for Jharkhand: 168 Rs/day for FY 2018-19; 174 Rs/day for FY2018-19 for Madhya Pradesh. For more details, see Appendix C.5.

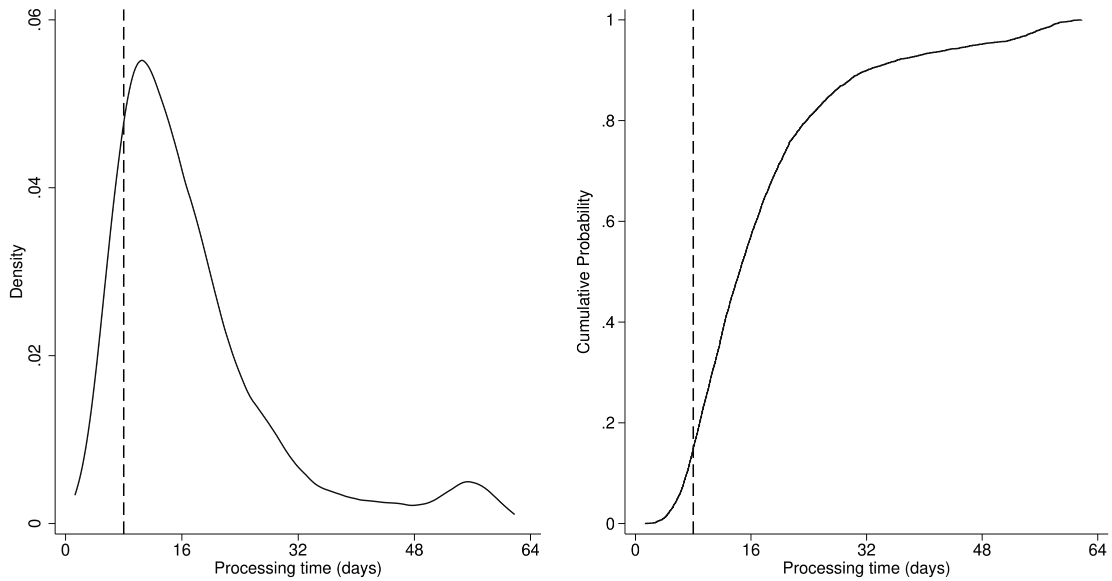
Appendix A: Additional Figures and Tables

Figure A1: MGNREGS Work, Verification, and Payment Process



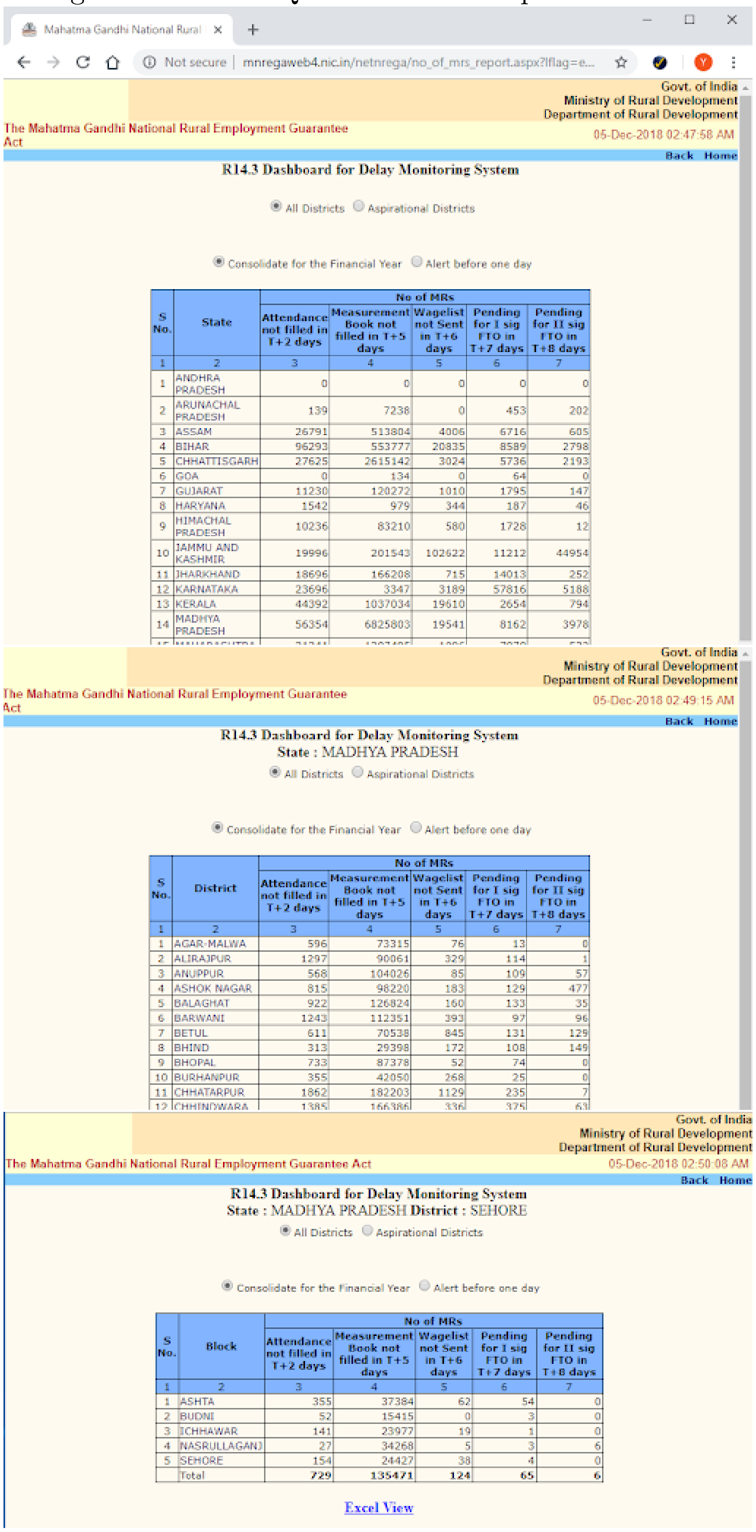
Notes: The figure shows a stylized representation of MGNREGS participation, work verification, and payment processing.

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

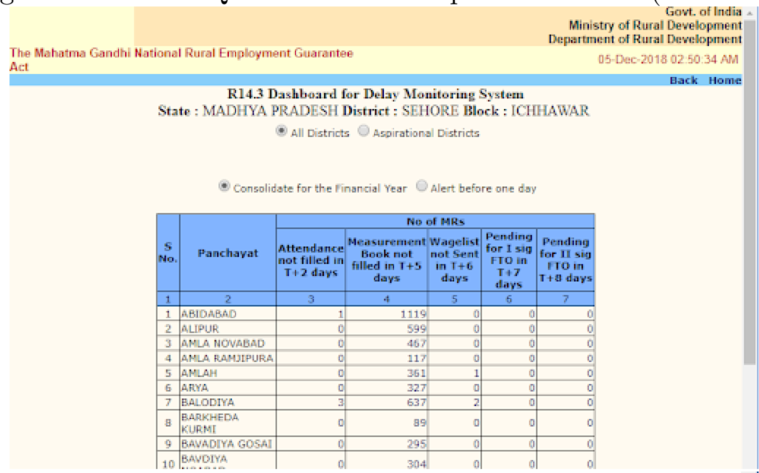
Consolidate for the Financial Year Alert before one day

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, accessed on December 5, 2018.

Figure A3: Status Quo Website Example Screenshots (continued)



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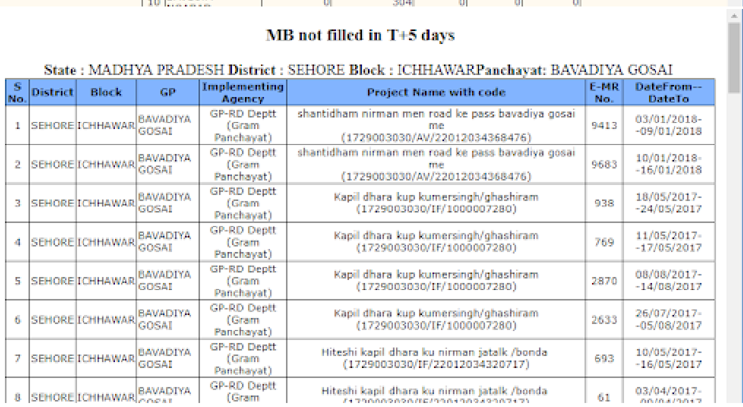
R14.3 Dashboard for Delay Monitoring System

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



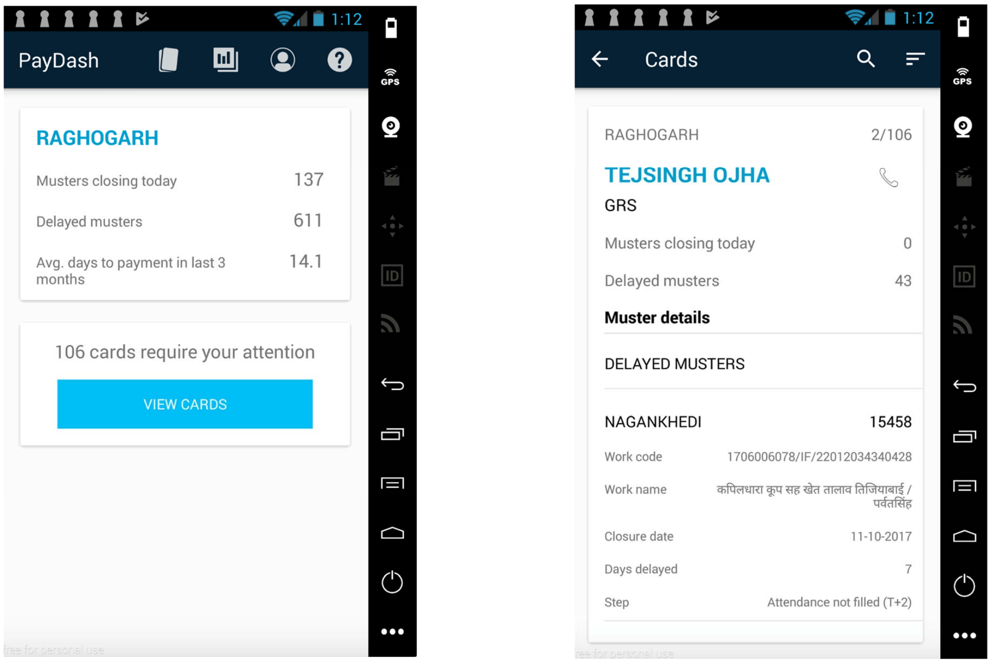
MB not filled in T+5 days

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, accessed on December 5, 2018.

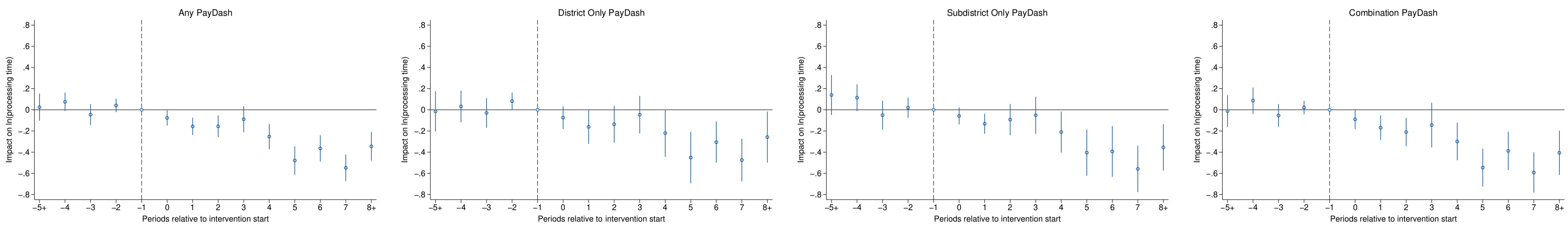
Figure A4: Subdistrict PayDash Example Screenshots



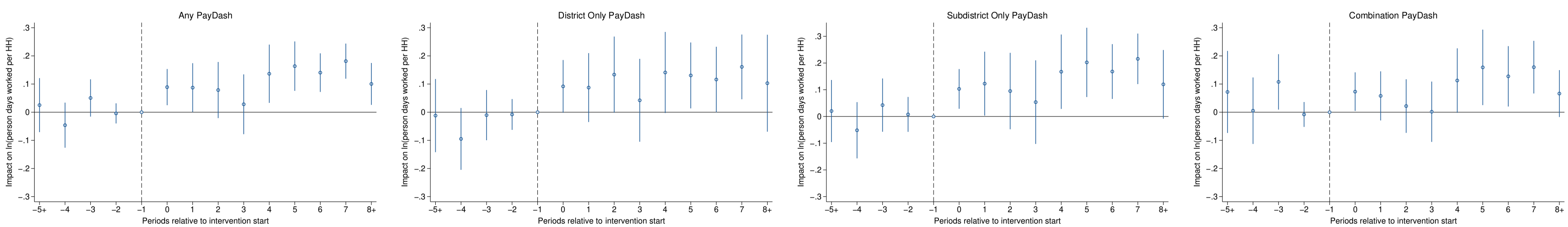
Notes: The figure shows an example subdistrict-level PayDash mobile application homescreen (left), providing a daily-updated overview of payment processing within a subdistrict officer's jurisdiction; and a "card" screen (right) with GP-by-subordinate-level information on pending delayed documents for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

Figure A5: Dynamics of PayDash Impacts - Treatment Arms

(a) Log processing time



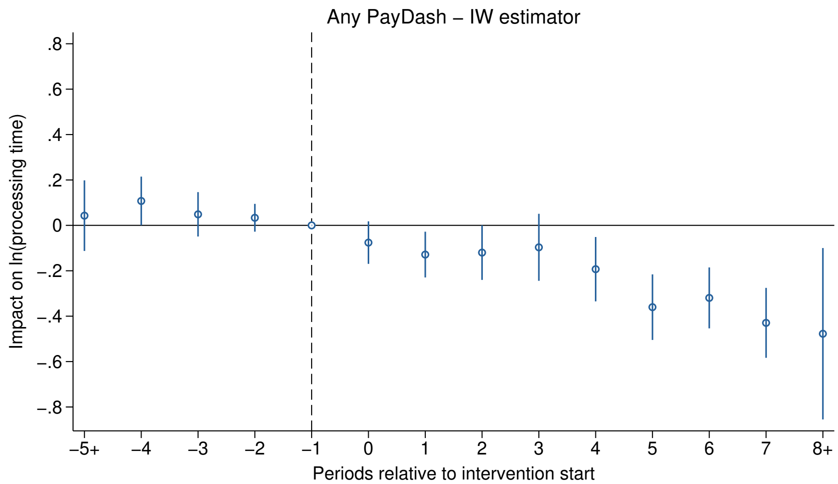
(b) Log days per working household



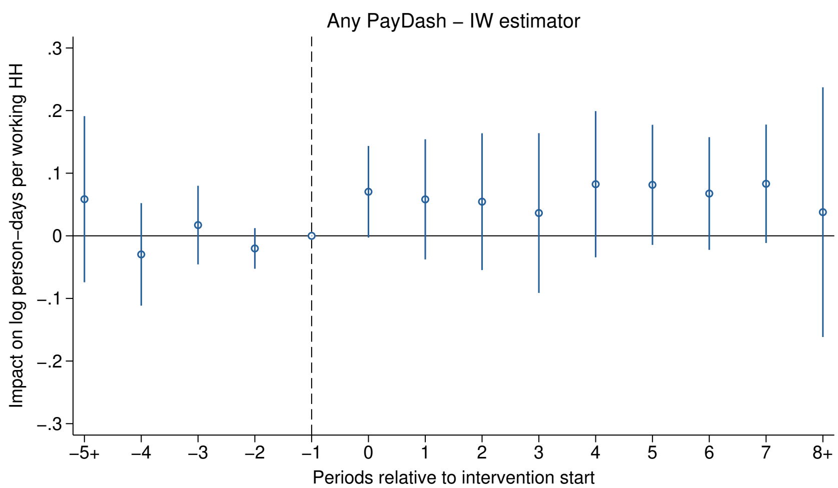
Notes: The figure shows event-study plots, constructed based on Equation (2) for the impacts of any PayDash provision and separately by PayDash treatment arm, with outcomes of log average processing time (Panel A) and log days per working household (Panel B). Standard errors in the underlying subdistrict-month-level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

Figure A6: IW Estimator

(a) Log processing time



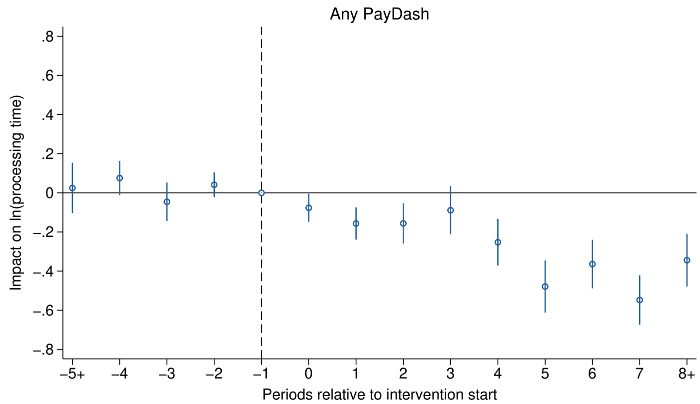
(b) Log days per working household



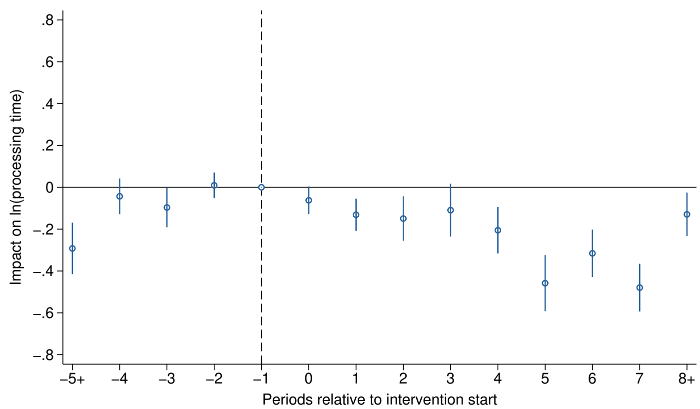
Notes: The figure shows event-study plots, constructed based on the corresponding Sun and Abraham (2021) interaction weighted (IW) estimator to Equation (2) for the impacts of any PayDash provision, with outcomes of log average processing time (Panel A) and log person-days per working household (Panel 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: Specification Comparison

(a) Baseline specification

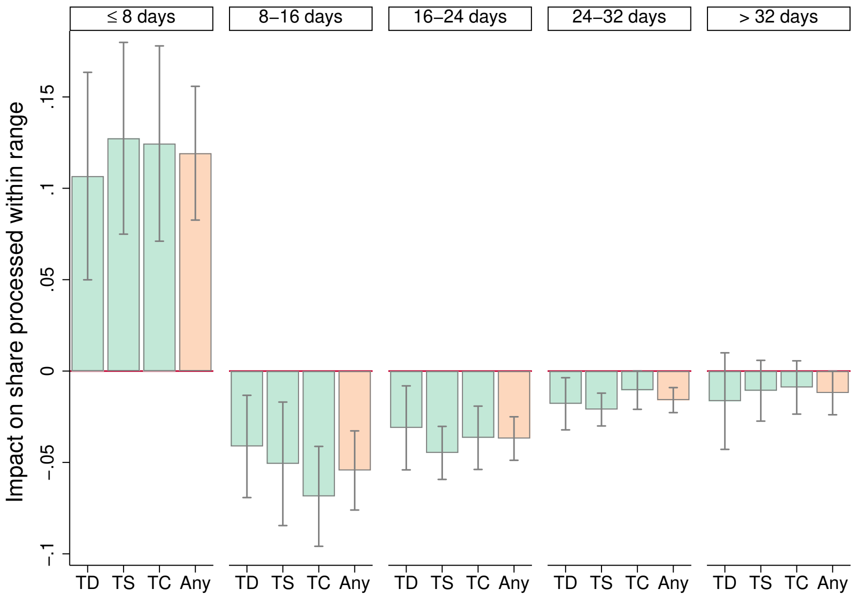


(b) Excluding trends



Notes: The figure shows event-study plots constructed based on Equation (2), excluding controls for district-specific linear time trends in Panel B, for the impacts of any PayDash provision on log average processing time. 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 A8: 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	1.47	-0.15	0.38	0.429	72
	[3.99]	(1.06)	(0.73)	(1.13)		
Total population (x1,000)	1420.60	-206.75	-144.76	-43.94	0.825	73
	[621.90]	(255.47)	(215.81)	(226.83)		
Rural population share	77.26	2.91	0.24	-3.13	0.602	71
	[15.88]	(4.81)	(5.56)	(5.26)		
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 officer 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)		
Workload index	0.00	-0.11	0.02	-0.17	0.515	135
	[0.63]	(0.15)	(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)		
Knowledge gap	0.38	-0.21*	-0.17	-0.22*	0.219	122
	[0.37]	(0.10)	(0.11)	(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)		
Workload index	-0.00	0.06	0.07	0.04	0.619	1023
	[0.54]	(0.05)	(0.06)	(0.06)		
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)		
Knowledge gap	0.45	0.02	-0.07	-0.04	0.690	935
	[0.80]	(0.10)	(0.07)	(0.07)		
Irregular local contact share	0.63	-0.08*	-0.08*	-0.07*	0.223	756
	[0.30]	(0.05)	(0.05)	(0.04)		

Notes: For the variables in each row, column (1) presents means and standard deviations. Columns (2)-(4) present coefficients and standard errors from regressions on treatment arm indicators (omitting control), 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 and column (6) gives the observation number. Standard errors are heteroskedasticity robust and, in Panels B and C, clustered by district. Panel A variables are district- or subdistrict-level, generated from administrative data for the year before rollout began (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 officer 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	3.85	0.06	0.01	0.04	0.956	121
	[0.43]	(0.14)	(0.12)	(0.10)		
PSM	4.34	0.15	0.29**	0.17	0.222	126
	[0.58]	(0.14)	(0.14)	(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	3.77	-0.03	0.02	0.01	0.797	922
	[0.46]	(0.06)	(0.05)	(0.04)		
PSM	4.25	-0.01	-0.05	-0.03	0.835	1005
	[0.59]	(0.05)	(0.06)	(0.05)		
Raven's	8.61	-0.14	0.26	0.44*	0.144	960
	[2.82]	(0.29)	(0.26)	(0.25)		

Notes: The first three variables are district-level monthly averages over the year before the intervention (February 2016-January 2017), generated from MGNREGS administrative data. See Table 1 notes for additional details on table construction.

Table A3: Analysis Plan Deviations

Pre-specified approach	Deviation	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 income over the previous year 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 payment processing times – both overall across steps under officer purview and by step – at locality-month level.	Omit step-specific measures as outcomes.	We were unable to obtain administrative data needed to generate step-specific measures.
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 by attendance registers in primary analysis. Present weighted analysis results in Appendix Table A6 for relevant outcomes, with subdistrict- and panchayat-month level observations.	Volume of attendance registers is itself potentially impacted by treatment, and maintain consistent specification across all main outcomes.
Equation (1) includes treatment indicators, subdistrict fixed effects, and month fixed effects. Also consider a version of Equation (1) that includes controls for characteristics at the level of district or subdistrict that may change over time for reasons unrelated to the intervention.	Include district-specific controls for linear time trends and quarter of year in primary analysis based on equation (1). Present results of analysis excluding controls in Appendix Table A4.	Controls for time trends address differential pre-trend observable in payment processing time event study analysis (see Appendix Figure A8), and use controls for quarter of year rather than time-varying characteristics to improve precision given relevance of seasonality in MGNREGS activity.
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, contact network structure, positive and negative perfomance incentive use.	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.
	Main analysis outcomes also include: above mandate length, attendance registers (Table 2); processing within time ranges (Fig 3); days worked per household (Table 3); payment request rejection, audit index (Table 4); and active worksites (Table 5).	These outcomes capture impacts on additional dimensions of program performance or shed light on underlying mechanisms. In some cases, datasets to generate these measures were only identfied later.
Main hypotheses regarding treatment impacts relate to district- and subdistrict-level PayDash, and complementarities between them.	Additionally hypothesize regarding potential substitutability between district and subdistrict PayDash.	We observed substitutability in impacts and collected information in follow-up surveys to examine underlying causes.
In treatment heterogeneity analysis, use each subcomponent and summary index form for Public Service Motivation and Big Five.	Use only summary indices for Public Service Motivation and Big Five.	Each index contains five sub-components; lacked clear theoretical justification for examining each subcomponent separately.

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

Table A4: PayDash Impacts - Robustness Checks

	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. 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	-0.235***	-0.123***	-0.753**	0.001	0.060	0.077	0.137	0.009
	(0.063)	(0.030)	(0.353)	(0.008)	(0.049)	(0.105)	(0.119)	(0.102)
Panel C. 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 D. Borusyak, Jaravel, and Spiess								
Any PayDash	-0.076**	-0.046**	-0.075	-0.012***	0.075***	-0.006	0.070	-0.004
	(0.031)	(0.018)	(0.223)	(0.004)	(0.023)	(0.064)	(0.074)	(0.079)
Panel E. 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)
Panel F. Post-rollout								
Any PayDash	-0.102***	-0.051***	-0.336***	0.015***	0.032	0.050	0.081	0.062
	(0.035)	(0.018)	(0.112)	(0.003)	(0.046)	(0.053)	(0.063)	(0.082)

Notes: Columns in Panel A report estimates following Equation (1) with the district-specific controls excluded. Columns in Panels B, C, D, and E report estimates based on the Sun and Abraham (2021), Callaway and Sant'Anna (2021), Borusyak, Jaravel, and Spiess (2024), and de Chaisemartin and D'Haultfoeuille (2024) estimators, respectively – averaging the estimated post-treatment period effects. Panel B additionally presents results from analysis including the district-specific controls, which is not possible for the estimators in Panels C through E. Columns in Panel F report estimates based on regressions of the listed outcome variable on a pooled treatment indicator and strata fixed effects, restricting the sample to post-rollout observations. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A5: Officer 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: District Officers						
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
Panel B: 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

Notes: Columns in each panel report means and standard deviations of the listed officer PayDash usage variable, calculated at the district-month (Panel A) or subdistrict-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)-numbered columns consider usage by program (chief executive) officers. Also shown are the coefficients on an indicator for PayDash provision at both administrative levels in regressions of the listed variables 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. Significant at *10 percent, **5 percent,***1 percent. "Sessions" includes both web and mobile usage, while "Duration" captures mobile usage only.

Table A6: Processing Time Impacts - Weighting by Attendance Registers

	Log processing time		Absolute deviation (days)		Share processed within 8 days	
	(1)	(2)	(3)	(4)	(5)	(6)
Any PayDash	-0.223***	-0.207***	-0.804***	-0.631***	-0.097***	-0.090***
	(0.047)	(0.045)	(0.260)	(0.148)	(0.022)	(0.021)
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	Above mandate length	Share processed within 8 days	Worker composition: Below poverty line	Worker composition: Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Pooled Treatment							
Any PayDash	-2.247***	0.041	-0.004	-0.236***	0.119***	0.006***	-0.002
	(0.484)	(0.091)	(0.008)	(0.042)	(0.018)	(0.002)	(0.003)
Control mean	12.784	5.868	1.853	0.695	0.483	0.180	0.381
Observations	13,443	13,443	13,443	13,443	13,443	13,443	13,443
Panel B: Impact Seasonality							
Any PayDash × High season	-0.304	0.144***	-0.003	0.022	-0.001	-0.001	-0.001
	(0.308)	(0.056)	(0.008)	(0.034)	(0.016)	(0.001)	(0.002)
Any PayDash	-2.150***	-0.009	-0.003	-0.241***	0.119***	0.006**	-0.002
	(0.491)	(0.083)	(0.008)	(0.041)	(0.018)	(0.002)	(0.003)
Any+Any×High, p-value	0.000	0.585	-0.007	0.000	0.000	0.012	0.357
Observations	13,443	13,443	13,443	13,443	13,443	13,443	13,443
Panel C: Treatment Arms							
District Only PayDash	-2.142**	0.064	-0.000	-0.223***	0.107***	0.007***	0.002
	(0.927)	(0.125)	(0.009)	(0.051)	(0.028)	(0.003)	(0.004)
Subdistrict Only PayDash	-2.536***	0.034	0.007	-0.207***	0.127***	0.004	-0.006
	(0.063)	(0.103)	(0.009)	(0.057)	(0.026)	(0.003)	(0.003)
Combination PayDash	-2.136**	0.025	-0.013	-0.269***	0.124***	0.006**	-0.004
	(0.703)	(0.132)	(0.013)	(0.069)	(0.027)	(0.002)	(0.005)
Coeff. equality, p-value	0.893	0.682	0.346	0.913	0.913	0.682	0.252
Observations	13,443	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. Control means in Panel A calculated over pre-intervention period. Panel B also presents the p-value for the total MGNREGS high season impact of Any PayDash and Panel C presents the p-value from a test of the equality of the treatment arm coefficients. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A8: PayDash Treatment Arms - Seasonal Heterogeneity

	Payment processing				Program scale			
	Log processing time	Share processed within 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 season								
× District Only PayDash	0.014	-0.022	-0.250	0.003	0.005	0.183***	0.189***	0.236***
	(0.035)	(0.016)	(0.190)	(0.005)	(0.026)	(0.047)	(0.048)	(0.075)
× Subdistrict Only PayDash	-0.008	-0.004	-0.200	0.003	0.027	0.097	0.124**	0.193***
	(0.054)	(0.023)	(0.280)	(0.005)	(0.026)	(0.059)	(0.055)	(0.060)
× Combination PayDash	-0.056	0.017	-0.240	0.003	0.027	0.131*	0.193***	0.196***
	(0.046)	(0.018)	(0.225)	(0.005)	(0.026)	(0.067)	(0.060)	(0.055)
District Only PayDash	-0.253***	0.108***	-1.194**	0.004	0.109***	-0.040	0.070	0.004
	(0.070)	(0.029)	(0.465)	(0.006)	(0.029)	(0.086)	(0.104)	(0.090)
Subdistrict Only PayDash	-0.254***	0.127***	-0.926**	-0.010	0.099***	-0.078	0.020	0.089
	(0.064)	(0.026)	(0.396)	(0.007)	(0.032)	(0.058)	(0.063)	(0.109)
Combination PayDash	-0.285***	0.121***	-1.100**	0.012	0.042	-0.102	-0.059	-0.047
	(0.062)	(0.026)	(0.418)	(0.006)	(0.028)	(0.094)	(0.091)	(0.078)
D + D × High, p-value	0.001	0.004	0.002	0.469	0.000	0.192	0.052	0.097
S + S × High, p-value	0.002	0.001	0.031	0.943	0.000	0.844	0.142	0.051
C + C × High, p-value	0.000	0.000	0.012	0.932	0.011	0.836	0.294	0.196
Observations	13,443	13,443	13,443	13,177	13,443	13,443	13,443	11,693

Notes: Columns report estimates following Equation (1), replacing the pooled treatment indicator with treatment-arm-specific indicators and additionally including an MGNREGS high season indicator (not shown) and its interactions with the treatment-arm-specific treatment indicators. The table also presents for each treatment arm the p-value for the total MGNREGS high season impact. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A9: Audit Impacts - Index Components and Officer Issues

	Index components				Officer-related issue		
	Any financial deviation	Any financial misapprop.	Any grievance	Any process violation	GP level	Subdistrict level	District level
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Pooled Treatment							
Any PayDash	-0.011	-0.006	-0.011	-0.009	-0.018	0.003	-0.000
	(0.025)	(0.015)	(0.019)	(0.035)	(0.028)	(0.009)	(0.000)
Control mean	0.122	0.102	0.135	0.192	0.126	0.018	0.000
Observations	20,621	20,621	20,621	20,621	20,621	20,621	20,621
Panel B: Treatment Arms							
District Only PayDash	0.004	0.004	-0.007	0.010	0.005	0.011	-0.000
	(0.027)	(0.017)	(0.026)	(0.043)	(0.035)	(0.012)	(0.000)
Subdistrict Only PayDash	-0.011	-0.010	-0.002	-0.017	-0.032	-0.010	-0.000
	(0.025)	(0.015)	(0.022)	(0.035)	(0.028)	(0.010)	(0.000)
Combination PayDash	-0.026	-0.012	-0.024	-0.019	-0.026	0.009	-0.000
	(0.025)	(0.016)	(0.019)	(0.037)	(0.030)	(0.012)	(0.000)
Coeff. equality, p-value	0.074	0.279	0.412	0.599	0.351	0.115	0.520
Observations	20,621	20,621	20,621	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. “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.

Table A10: Impacts on Subdistrict Posting Transfers - Longer Term

	Officer posting transfer	
	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
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 the p-value from a test 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 A11: Heterogeneity in PayDash Impacts by Officer Characteristics

Attribute:	Log processing time					Log person-days per working household				
	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	-0.019	0.064	-0.073	-0.060	-0.067	0.006	0.072	0.094*	-0.021	0.003
	(0.013)	(0.227)	(0.164)	(0.076)	(0.059)	(0.005)	(0.085)	(0.053)	(0.031)	(0.018)
Any PayDash	-0.104	-0.315*	-0.230**	-0.043	0.014	0.037	0.037	0.030	0.167	0.076
	(0.125)	(0.173)	(0.110)	(0.302)	(0.254)	(0.046)	(0.068)	(0.039)	(0.124)	(0.081)
Observations	12,651	12,699	12,963	11,908	12,795	12,651	12,699	12,963	11,908	12,795
ii. Above median										
Any PayDash										
× Attribute	-0.152*	0.052	-0.061	-0.076	0.036	0.064**	0.042	0.034	-0.069**	-0.031
	(0.081)	(0.091)	(0.083)	(0.078)	(0.076)	(0.030)	(0.042)	(0.033)	(0.032)	(0.033)
Any PayDash	-0.183**	-0.307***	-0.234***	-0.233***	-0.290***	0.052*	0.059	0.065**	0.120***	0.105***
	(0.072)	(0.085)	(0.073)	(0.064)	(0.063)	(0.026)	(0.039)	(0.028)	(0.027)	(0.025)
Observations	12,651	12,699	12,963	11,908	12,795	12,651	12,699	12,963	11,908	12,795
Panel B. Subdistrict PO										
i. Continuous										
Any PayDash										
× Attribute	-0.005	0.113	-0.040	-0.036	0.018	0.002	0.008	-0.025	-0.005	-0.002
	(0.005)	(0.050)	(0.071)	(0.031)	(0.027)	(0.003)	(0.029)	(0.041)	(0.014)	(0.012)
Any PayDash	-0.307***	-0.345***	-0.243***	-0.122	-0.339***	0.077**	0.085***	0.106***	0.112*	0.102*
	(0.044)	(0.051)	(0.052)	(0.123)	(0.126)	(0.034)	(0.029)	(0.032)	(0.058)	(0.054)
Observations	12,174	12,366	12,462	11,648	12,462	12,174	12,366	12,462	11,648	12,462
ii. Above median										
Any PayDash										
× Attribute	0.018	0.071**	0.004	-0.023	0.059*	0.010	-0.011	-0.009	-0.001	-0.014
	(0.030)	(0.031)	(0.032)	(0.026)	(0.031)	(0.018)	(0.014)	(0.018)	(0.013)	(0.016)
Any PayDash	-0.276***	-0.311***	-0.268***	-0.247***	-0.296***	0.085***	0.098***	0.098***	0.095***	0.100***
	(0.037)	(0.044)	(0.032)	(0.042)	(0.043)	(0.023)	(0.021)	(0.025)	(0.022)	(0.023)
Observations	12,174	12,366	12,462	11,648	12,462	12,174	12,366	12,462	11,648	12,462

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. XXADD VARIABLE CONSTRUCTION DETAILSXX

Table A12: Heterogeneity by Administrative Structure and Workload - Treatment Arms

	Log processing time	
	(1)	(2)
District Only PayDash		
× High GPs per subdistrict	-0.316**	
	(0.146)	
× High subdistrict PO workload		-0.339***
		(0.122)
District Only PayDash	-0.135***	-0.113**
	(0.050)	(0.054)
Subdistrict Only PayDash		
× High GPs per subdistrict	-0.153	
	(0.129)	
× High subdistrict PO workload		-0.202
		(0.168)
Subdistrict Only PayDash	-0.179	-0.132
	(0.108)	(0.152)
Combination PayDash		
× High GPs per subdistrict	-0.033	
	(0.115)	
× High subdistrict PO workload		-0.055
		(0.121)
Combination PayDash	-0.277***	-0.272***
	(0.086)	(0.082)
Observations	12,629	12,629
D + S = C, p-value (high)	0.009	0.004
D + S = C, p-value (low)	0.791	0.878
D = S = C, p-value (high)	0.656	0.589
D = S = C, p-value (low)	0.303	0.216
Control outcome mean (high)	2.69	2.52
Control outcome mean (low)	2.30	2.31

Notes: All columns report estimates following Equation (1) with additional terms included as described subsequently. Column (1) also includes an interaction of the treatment arm indicators with an indicator for being an above-median district in terms of average number of panchayats per subdistrict. Column (2) also includes an interaction of the treatment arm indicators with an indicator for being an above-median district in terms of the average value of the baseline subdistrict PO workload index. "D + S = C" corresponds to a test of the equality of the sum of the District Only PayDash and Subdistrict Only PayDash coefficients with the Combination coefficient, "D = S = C" corresponds to a test of the equality of all three coefficients, with "high" and "low" denoting respectively the sets of above- and below-median districts in terms of average GP-to-subdistrict ratio in column (1) and average baseline PO workload index value in column (2). Control means calculated over the pre-intervention period, with "high" and "low" corresponding respectively to above- and below-median districts in terms of average number of panchayats per subdistrict in columns (1) and in terms of average baseline subdistrict PO workload index in column (2). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A13: Association of Administrative Structure and Workload

	Workload index			
	Subdistrict officers		District officers	
	(1)	(2)	(3)	(4)
High GPs per subdistrict	0.202**		0.179	
	(0.089)		(0.191)	
High subdistricts per district	-0.049		0.069	
	(0.070)		(0.153)	
GPs per subdistrict		0.008**		-0.006
		(0.003)		(0.006)
Subdistricts per district		0.003		-0.001
		(0.007)		(0.020)
Outcome mean	0.004	0.004	-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 an indicator for being an above-median district in terms of average number of panchayats per subdistrict and an indicator for being an above-median district in terms of number of subdistricts. Columns (2) and (4) report estimates from regressions at the baseline program officer level of the listed variable on the district-level average number of panchayats per subdistrict and the number of subdistricts. Also included in all regressions is a state indicator. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A14: Heterogeneity by Administrative Structure and Workload - Alternative Measures

	Log processing time			
	(1)	(2)	(3)	(4)
Panel A: Within-State Measure				
Any PayDash				
× High GPs per subdistrict	-0.091	-0.125		-0.069
	(0.076)	(0.090)		(0.085)
× High subdistrict workload			-0.223***	-0.214**
			(0.065)	(0.073)
Any PayDash	-0.233***	0.863	-0.159***	-0.492
	(0.054)	(1.140)	(0.045)	(0.991)
Observations	12,629	12,629	12,629	12,629
Interacted additional controls		X		X
Panel B: Continuous Measure				
Any PayDash				
× GPs per subdistrict	-0.002	-0.007*		-0.006*
	(0.002)	(0.004)		(0.003)
× Subdistrict PO workload			-0.312***	-0.417***
			(0.113)	(0.135)
Any PayDash	-0.148	1.333	-0.262***	0.687
	(0.095)	(1.411)	(0.044)	(1.207)
Observations	12,629	12,629	12,629	12,629
Interacted additional controls		X		X

Notes: All columns report estimates following Equation (1) with additional terms included as described subsequently. In Panel A: Columns (1), (2), and (4) include 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. Columns (3) and (4) include an interaction of the treatment indicator with an indicator for being an above-state-median district in terms of the average value of the baseline subdistrict PO workload index. Columns (2) and (4) additionally include interactions (not shown) of the treatment indicator with an indicator for being an above-state-median district in terms of number of subdistricts, a Jharkhand state indicator, district-level measures of rural population share and log population, baseline district PO post-graduate education completion and daily MIS usage, and the district-level baseline average post-graduate education completion and and daily MIS usage for subdistrict POs. In Panel B: Columns (1), (2), and (4) also include an interaction of the treatment indicator with the district-level average number of panchayats per subdistrict. Columns (3) and (4) also include an interaction of the treatment indicator with the average value of the baseline subdistrict PO workload index. Columns (2) and (4) additionally include interactions (not shown) of the treatment indicator with number of subdistricts, a Jharkhand state indicator, district-level measures of rural population share and log population, baseline district PO post-graduate education completion and daily MIS usage, and the district-level 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 A15: Heterogeneity by Administrative Structure and Workload - PayDash Usage

	Subdistrict POs				District POs			
	Sessions		Duration (min)		Sessions		Duration (min)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High:								
Subdistrict PO workload	1.41*	1.59	15.29**	17.21**		-0.95		-4.22
	(0.79)	(0.96)	(6.51)	(6.83)		(1.54)		(8.18)
GPs per subdistrict		-1.06		-6.83		3.30*		16.99
		(0.99)		(6.95)		(1.82)		(11.92)
District PO workload		0.98		1.75	-1.95	-2.19	-14.31	-15.49
		(0.74)		(4.56)	(1.65)	(1.48)	(9.89)	(9.92)
Subdistricts per district		-0.29		2.66		-3.02		-11.33
		(1.67)		(11.18)		(1.82)		(11.32)
Both levels PayDash	1.16	0.93	6.12	5.54	-1.83	-3.34*	-18.30	-25.02
	(0.81)	(0.83)	(6.28)	(6.43)	(1.92)	(1.95)	(14.45)	(16.27)
Observations	3,716	3,716	3,716	3,716	487	487	487	487
Outcome mean	3.68	3.68	21.58	21.58	3.82	3.82	19.57	19.57

Notes: Columns (1) through (4) report estimates from regressions at the subdistrict-month level of the listed program officer PayDash usage variable on an indicator for being an above-median district in terms of average value of the baseline subdistrict PO workload index. Additionally included in the regressions in columns (2) and (4) are indicators for being an above-median district in terms of average number of panchayats per subdistrict, baseline district PO workload index, and number of subdistricts. Columns (5) through (8) report estimates from regressions at the district-month level of the listed program officer PayDash usage variable on an indicator for being an above-median district in terms of the baseline district PO workload index. Additionally included in the regressions in columns (6) and (8) are indicators for being an above-median district in terms of average value of the baseline subdistrict PO workload index, average number of panchayats per subdistrict, and number of subdistricts. Regressions in all columns also include month and strata fixed effects and an indicator for PayDash provision at both officer levels. The sample in each column is restricted to treatment months in localities receiving PayDash at the corresponding officer level. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A16: Heterogeneity by Workload and Season

	Log processing time	Share processed “late” (>8 days)	Absolute deviation (days)	Log days per working household	Log days worked	Log active worksites
	(1)	(2)	(3)	(4)	(5)	(6)
Any PayDash						
× High workload	-0.181**	-0.073**	-0.766	0.061	0.061	0.059
	(0.078)	(0.033)	(0.521)	(0.037)	(0.096)	(0.095)
× High season	-0.045	-0.003	-0.383	0.061**	0.185***	0.199***
	(0.050)	(0.020)	(0.259)	(0.029)	(0.057)	(0.057)
× High workload × High season	0.024	-0.004	0.175	-0.065	-0.073	-0.011
	(0.060)	(0.027)	(0.337)	(0.041)	(0.091)	(0.115)
Any PayDash	-0.183***	-0.086***	-0.721**	0.048**	-0.025	-0.017
	(0.051)	(0.022)	(0.348)	(0.019)	(0.076)	(0.066)
Observations	13,443	13,443	13,443	13,443	13,443	11,693

Notes: All columns report estimates following Equation (1) with additionally included interactions of the treatment indicator with an indicator for being an above-median district in terms of the average value of the baseline subdistrict PO workload index (“High workload”), an MGNREGS high season indicator, and the interaction of the high workload and high season indicators. Also included (not shown) in all regressions are a high season indicator and the interaction of the high season and high workload indicators. 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.[38]

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

We characterize the pre-PayDash status quo as having sufficiently high c_M and c_P.[39] 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.*

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

[38] We assume that the manager exerts effort when indifferent to doing so.
[39] Specifically, $\frac{Y_1(\pi_1-\pi_0)^2}{\pi_1} \le c_M \le Y_1(\pi_1-\pi_0)$ and $c_P \ge \frac{Y_1\pi_0(\pi_1-\pi_0)}{\pi_1}$.

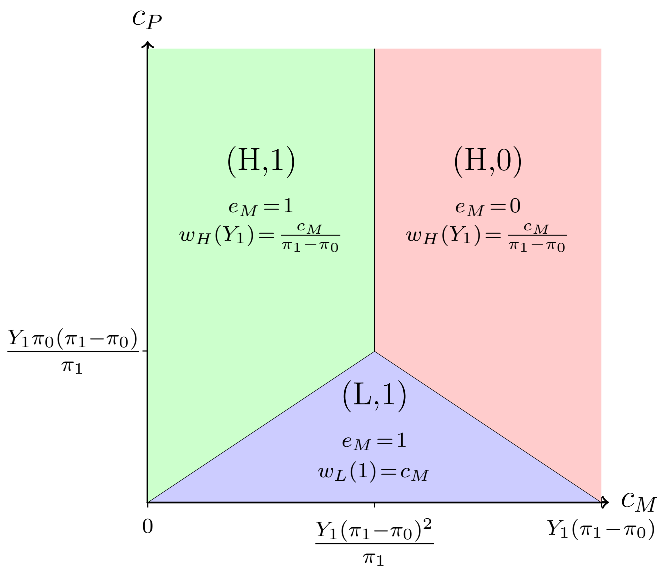


Figure B1: Equilibrium contracts with varying c_M,c_P

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:

$$\pi_1 w_H(Y_1) - c_M, \text{ for } e_M = 1$$

$$\pi_0 w_H(Y_1) + K, \text{ for } e_M = 0$$

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:

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

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.[40] 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.*
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.

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

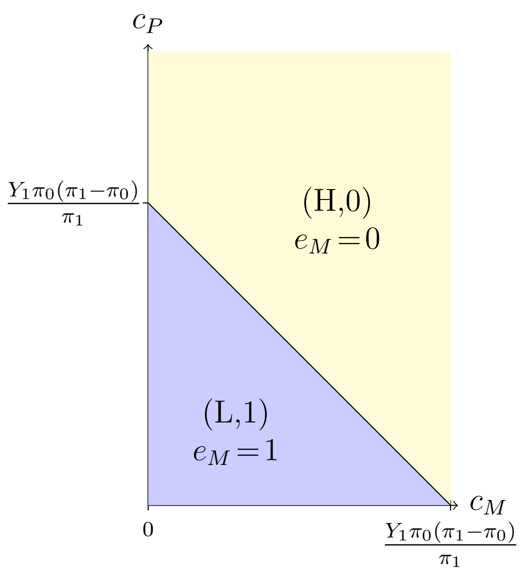


Figure B2: Equilibrium contracts under corruption, with $K=\frac{Y_1(\pi_1-\pi_0)^2}{\pi_1}$

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 officers to PayDash, we invited the relevant government officials – district and subdistrict CEOs and POs – in each training session cachement area to a half-day session. To avoid treatment contamination, officers from treatment areas were trained on separate days and/or locations from those in control areas. To avoid sensitivities related to officials' seniority, we conducted sessions separately not only for treatment and control officials, but also for block and district-level officials within these groups.

Both control and treatment officials went through the same training session process, with the exception that treatment officials were additionally introduced to and provided PayDash. First, we collected baseline survey data from all officials through a self-administered, paper survey. We then conducted a session outlining data-based management tools available to officials in the MGNREGS MIS and asked officials to share about their professional challenges as bureaucrats. After this, control officials were dismissed. In sessions with treatment officers, the training continued with an additional roughly one-hour session where officers were introduced to and instructed in how to use 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 all officials to report for this official training) to maximize the likelihood of officer presence at the training sessions during the state roll-out. For those officials that did not attend the group-based training, we 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 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. Reports include issues raised and officially filed in the Gram Sabha, as well as an audit checklist that records observations the auditors made during visits with rural households listed in MGNREGS administrative data and to worksites, and through their review of relevant documentation. Departments can then choose to take action against offenders named in the audit reports, and issues filed are only resolved when action has been taken to address and compensate for the problem raised.

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 analysis comparing benefits and costs of PayDash, we utilize actual cost data reflecting the amount spent on initial PayDash web and Android app development and testing, incorporating costs of maintenance as incurred through the first full year of the RCT, reflecting no additional investments in app-related retraining or improvements.

We estimate benefits that accrue directly and indirectly to MGNREGS workers. For direct benefits, we compute the total amount of additional wages paid to workers as a result of PayDash access, using the state-specific worker wage rates of 168 Rs. per day for Jharkhand and 174 Rs. per day for Madhya Pradesh, the official wage rates paid in the year of the RCT roll-out (the 2018-19 fiscal year).

To calculate estimated indirect benefits to workers due to declines in wage payment delays, we apply treatment effect estimates that suggest improvements in 2.59 days to payment overall; we assume 80% of this improvement is passed through in terms of final time to payment (motivated by the correlation of 0.8 between final payment deposit and stage one processing times), resulting in slightly over 2 days in reduced time to payment. To quantify these improvements in terms of benefits conferred to citizens, we assume that these improvements allow for fewer days of loan-financed household expenditure in treatment areas compared to the non-PayDash counterfactual. This assumption reflects anecdotal evidence that impoverished households awaiting irregular MGNREGS payments take loans to support short-term consumption smoothing until payments arrive. These loans sometimes are granted by local leaders and generally have unfavorable terms; our estimates of loan costs averted more conservatively rely on official estimates on loan terms reported in the All India Debt and Investment Survey for 2019. We examine the terms of loans reported for non-business purposes by households that secured loans in 2018 or 2019 in Jharkhand and Madhya Pradesh. To more closely reflect the MGNREGS worker population, we examine loan terms for households that fall in the bottom two quintiles of consumption expenditure.

To estimate the size of a loan needed to finance three days 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 and reaching the household's basic consumption needs for three days by computing the average household-level consumption need by assuming the average rural household in these states had 4.2 members on average (reflecting data from the 2019 All-India Debt and Investment Survey's household module, part of the National Sample Survey.) We then inflate this poverty line to 2019 dollars using India's CPI for rural India as issued by the RBI.

Finally, we apply the mean loan term for households from Madhya Pradesh and Jharkhand residing in the bottom two consumption expnediture quintiles, 20% with a compound interest structure. This approach is relatively conservative, as the modal loan of non-zero interest includes a 24% annual rate. (We restrict to loans secured in 2018 and 2019, again as reported in the All-India Debt and Investment Survey.) We assume households take a loan for three days of needed consumption and the loan is outstanding for two weeks, with no pre-payment fees or penalties. All amounts are converted to dollars using the exchange rate on the first day of the 2018-19 fiscal year as reported by oanda.com.