Updating the State: Does Easier Access to Program Information Improve Bureaucrat Performance?

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April 2024

Abstract

We conduct an at-scale field experiment with two large Indian state governments, providing administrators of India's flagship rural workfare program access to a digital platform ("PayDash") that lowers the costs of acquiring management-relevant information. We vary the levels of the bureaucratic hierarchy receiving PayDash to study the importance for program performance of middle managers' workload versus upper-level principals' ability to monitor them. PayDash reduces payment processing times for program participants by 11% and increases their days worked through the program by 19%, without worsening corruption detected by external audits. Impacts are indistinguishable when PayDash is provided to principals versus middle managers, with no additional gains when given to both levels. Our findings indicate that lowering the costs of information acquisition within the bureaucracy improves program performance primarily by freeing middle-manager bandwidth. Additionally, middle-manager transfers fall by 20% when principals receive PayDash, consistent with a shift away from blunt incentive contracts.

JEL Codes: D73, I38, M59, O15, C93

*We thank Lydia Assouad, Fred Finan, François Gerard, Sergei Guriev, Syeda ShahBano Ijaz, and numerous seminar participants for comments. For project and research support, we thank Jenna Allard, Kartikeya Batra, Geet Chawla, Parth Chawla, Fikremariam Gedefaw, Raul Duarte Gonzalez, Akshat Goel, Anuska Jain, Siddharth Jain, Prachi Jadhav, Mahreen Khan, Annanya Mahajan, Sitanshu Mishra, Sayantan Mitra, Sitaram Mukherjee, Prakhar Saxena, Aparna Singh, Shreya Singh, Sam Solomon, and Ramita Taneja. For software development, we thank Naman Dwivedi, Prempal Singh, and Ravi Suhag. We thank the Economic Development and Institutions Program, Gates Foundation, J-PAL Governance Initiative, and the National Science Foundation for financial support. AEA RCT Registry is AEARCTR-0001292. Author affiliation: IDinsight (Dodge), University of Michigan (Neggers), and Yale University (Pande and Troyer Moore).

1 Introduction

The effectiveness of delegated governance depends on the quality of information flows inside the organization (Dixit 2002; Aghion and Tirole 1997; Mookherjee 2006). Supervisory principals and middle managers need accurate information to effectively oversee their subordinates. In the private sector, new technologies that impact managers' informational advantage often change the extent of decentralization within firms and impact firm entry and exit, while typically improving productivity (Acemoglu et al. 2007). In contrast, the public sector is long-lived and has a monopoly on its tasks, making its organizational structure less responsive to new technology.[1] In recent years, digital technology has transformed delivery of social protection programs administered by the public sector, also potentially making it easier to track resource flows and performance.[2] In this paper, we study how, if at all, greater ease of accessing program information for administrators can be leveraged to improve service delivery, holding the architecture of the public sector fixed.

This paper considers this question in the context of India's largest social protection program, the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS).[3] Recent research examines how digital technologies in the MGNREGS setting can enhance state capacity by reducing village official and senior bureaucratic discretion over resource allocation (Banerjee et al. 2015; Muralidharan et al. 2016). The impacts of easier access to program information on bureaucratic efficiency and program performance has received less attention. This paper examines how data generated by digital payment systems for MGNREGS can be used to improve information flows within the administrative hierarchy. We study how these changes influence MGNREGS beneficiaries' payment processing delays and, relatedly, citizens' program participation.

We conducted an at-scale field experiment with over 1,200 district and subdistrict MGNREGS administrators in Madhya Pradesh and Jharkhand, two North Indian states with

[1] In our setting, the administrative structure and duties to be performed at different levels of the administrative hierarchy were mandated through a 2005 Act of Parliament that established MGNREGS. Globally, civil service organizational structure–including rules for recruitment, positions and hierarchies, promotions, and more–is typically defined via formal codes or acts.

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

[3] Over 50 million rural households participated nationally in MGNREGS in 2019-20, at a cost of roughly US $10 billion. Multiple studies document MGNREGS' positive impacts on these households' well-being (Deininger and Liu 2013; Imbert and Papp 2012; Klonner and Oldiges 2014; Muralidharan et al. 2018).

120 million people, 25 million of whom are rural poor.[4] In each state, a within-district bureaucratic hierarchy is responsible for program administration: district officials oversee MGNREGS and constitute the principals for program implementation. Subdistrict officers function as middle managers, authorizing MGNREGS worker payments and monitoring village council, or Gram Panchayat (GP), officials who select workers, implement program works, and collect information on work completed. In the year before the intervention, MGNREGS participants in our study states worked 172 million person-days and officials within the district hierarchy took an average of 18 days to process worker payments, compared to the central government's stipulated 8-day processing mandate. Payment processing delays at the bureaucratic stage are highly correlated (0.82) with delays in overall time to payment delivery.[5]

In collaboration with government partners, we developed "PayDash", a low-cost, mobile- and web-based management platform for MGNREGS officials. It uses digital exhaust – timestamps capturing user activity in the MGNREGS digital administrative system – to track progress in the steps underlying worker payment processing. PayDash aims to reduce time costs associated with learning about delays and who is responsible by making information more accessible and actionable than the current government website interface, in part by better tailoring information presented to the specific needs of officers.

Whether lowering costs of administrator access to management-relevant information affects program performance depends on the nature of agency concerns. If the main bottleneck is a lack of knowledge about frontline implementation challenges among middle managers and the principal, lowering information search costs for either group could improve program performance. If middle management shirking or rent-seeking is the primary concern, improving the principal's information is key. Separately, if the principal's goal in designing incentive contracts for middle managers is to minimize her effort costs, improving her information can reduce use of high-powered incentive contracts (Carroll and Bolte 2023). In low-income bureaucracies, the canonical example of such an incentive is the use of posting transfers (Iyer and Mani 2012; Khan et al. 2019). To examine these possibilities, we randomly allocated districts to control or one of three PayDash bureaucratic treatment groups: district-level (relevant principal), subdistrict-level (middle manager), or both.

[4] Districts are the highest within-state administrative unit.

[5] Following payment authorization, banks process requests and deliver payment to worker accounts.

Our analysis uses multiple data sources. At baseline, we surveyed all study participants. We subsequently assessed treated participants' PayDash engagement using Google analytics and endline surveys with a subset of officials. Processing-time based MGNREGS performance measures come from 19.5 million worker attendance registers issued for works projects in our study states, spanning the years before and during the intervention. Additional administrative datasets and external village-level audits allow us to measure MGNREGS work provided, quality, corruption, and community MGNREGS demand. Finally, we tracked officer transfers throughout the intervention.

Turning to our findings, first, district and subdistrict bureaucrats use PayDash on roughly a weekly basis on average. Second, PayDash benefits MGNREGS workers with no adverse impacts on work quality. Bureaucrats in treatment districts completed payment processing procedures 1.4 days faster than in control districts (11% at baseline), with a reduction in variability as well. Beneficiary person-days worked rose 19% in treatment districts. The share of government-submitted payment requests rejected by banks, which indicates bureaucrat work quality and impacts overall payment delivery time, did not change, nor did program irregularities reported by external auditors, including financial misappropriation. Third, districts where the principal received PayDash saw an 11 percentage point (23%) decline in subdistrict-level middle manager transfers.

Treatment arms show similar impacts on average processing time and beneficiary days worked, regardless of the administrative level provided PayDash. PayDash also improved middle managers' accuracy in assessing their jurisdictions' payment processing performance by 19%, with no difference across treatment arms. The similarity of effects across middle-manager and principal provision points against agency concerns being the primary constraint at the middle-manager level. Furthermore, providing PayDash to both the district and subdistrict levels has the same impact as giving access to either level alone. In endline surveys, consistent with this substitutability, the majority of treated district officers reported sharing management-relevant information from PayDash with their subordinates. Finally, the one primary outcome where impacts vary by treatment arm is middle manager transfers, which only decline when district officials receives PayDash.

Together with the fact that the information provided by PayDash was available for the control group with higher effort costs through the existing government website, we interpret this pattern of results as pointing to the value of the information provided through the platform. Multiple pieces of ancillary evidence bolster this interpretation. First, usage of PayDash declined across treatment arms during a roughly month-long exogenous mid-intervention data outage which left the in-app contact features functional, while ceasing the availability of up-to-date processing time information. Second, if lower information acquisition costs were the primary reason for the intervention's observed impacts, these effects should be larger when officer workload is higher. Here, we exploit arguably exogenous variation in the number of village administrative (GP) units under the purview of a middle manager, which can be traced to the fact that subdistrict boundaries have remained largely unchanged since independence, while GP boundaries are regularly configured to maintain similar population size. At baseline, processing delays are more severe and middle managers have higher workload index scores in districts where middle managers oversee more GPs. We find that the treatment impacts of PayDash on payment processing times are concentrated in these high-GP-ratio subdistricts.

Our research contributes to a growing body of evidence on how weak information flows within administrative hierarchies impact the quality of public service delivery (Finan et al. 2017). A primary focus of this literature has been on the value of improving top-down monitoring to discipline middle- and lower-level officials in the presence of moral hazard, and when such efforts may fail.[6] More recent work underscores the importance of information available to middle managers. Dal Bó et al. (2021), for instance, show that mid-level supervisors hold information unobservable to higher-level principals that, when leveraged appropriately, can improve service delivery and reduce frontline agent shirking.[7] To the best of our knowledge, our study is the first to study the relevance of agency concerns as compared to information constraints for middle management by experimentally varying information acquisition costs at different levels of the bureaucratic hierarchy.[8] Our findings are consistent with recent studies that suggest mid-level agency concerns are less critical and instead highlight the value of bureaucrat autonomy (Rasul and Rogger 2018; Bandiera et al. 2021). Our findings highlight the value of lowering information acquisition costs for service delivery when bu-

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

[7]See also Fenizia (2022) which highlights the relevance of middle managers in social security office performance in Italy, and Rasul et al. (2020) which identifies variation in project completion rates in Ghana based on the management practices of mid-level bureaucrats.

[8]Deserranno et al. (2020) vary financial incentives at multiple levels and find effort complementarities.

reaucratic workloads are high.[9] Recent work indicates that high workloads are common in the low capacity administrative contexts typical of lower-income countries.[10]

Information is relevant to the bureaucrat herself and for cross-level cooperation. In this sense, we connect to work examining the value of mission in aligning incentives across levels, where bureaucrats act as motivated agents that serve the needs of citizens (Besley and Ghatak 2005; Prendergast 2007), and the importance of trust and social capital in delegation (Bloom et al. 2012).[11] Finally, in contrast to Mattsson (2021), improved information on program implementation strengthens program performance without increasing corruption.

The paper is organized as follows. Section 2 describes the context, conceptual framework, and intervention. Section 3 describes the data and empirical strategy. Section 4 presents findings on the impacts of PayDash on MGNREGS program performance and administration, and Section 5 provides evidence on mechanisms. Section 6 concludes.

2 Context and Intervention

Through MGNREGS, rural households in India are entitled to 100 days of paid work annually, typically on labor-intensive rural infrastructure projects. MGNREGS projects are funded by the federal government and implemented by Indian states. We first describe below MGNREGS implementation and challenges faced. We then provide the conceptual framework, followed by details of the PayDash digital information platform and our intervention design.

2.1 MGNREGS administration

Below the overarching state level, MGNREGS activities are implemented and monitored within a three-tier administrative hierarchy composed of officials at the district, subdistrict, and Gram Panchayat (GP) levels. Figure A1 provides a visual overview.

[9] Aman-Rana et al. (2022) considers adverse impacts of underfunding in bureaucracies in South Asia, including rent extraction to partially fund service delivery.

[10] Rogger (2017) provides cross-country survey evidence that bureaucrats in low- and lower-middle-income countries commonly work overtime. Dasgupta and Kapur (2020) find in India that middle managers are heavily under-resourced relative to their responsibilities, negatively impacting social protection program implementation. Other studies consider issues of overwork and approaches to addressing it among frontline agents delivering public services (Jewell and Glaser 2006; Tummers et al. 2015).

[11] We also connect to work considering conditions under which contracts can be designed to elicit effort to help a colleague (Itoh 1991) or otherwise cooperate to achieve an organizational objective (Itoh 1992).

GP-level agents initiate MGNREGS project worksites and select workers. For each six-day work cycle ("workspell") at a worksite, the local Gram Rozgar Sevak (GRS) enters worker details and attendance in an attendance register ("muster roll"). After the associated work completed is ratified by a subdistrict-based engineer, the GRS inputs attendance register and work completion information into the web-based MGNREGS Management Information System (MIS) for review at the subdistrict level.

The subdistrict Program Officer (PO) and the Chief Executive Officer (CEO) supervise work verification and payment processing.[12] They also provide input into MGNREGS project selection and can help publicize available work (Gulzar et al. 2017). As the highest ranking officer in charge of MGNREGS oversight, the PO manages frontline agents and reviews their attendance register and work verification submissions.[13] She reports to the CEO, the subdistrict's highest ranking bureaucrat, who oversees multiple programs and has relatively less involvement in MGNREGS routine management. After reviewing the information associated with an attendance register, subdistrict officers digitally sign a funds transfer order (FTO) for worker wage payments, completing Stage 1 of payment processing. In Stage 2, the federal government's electronic funds management system (PFMS) routes payment requests to a bank, which deposits funds into workers' bank accounts. If payment transfers fail to complete, a "rejected FTO" is generated and flagged in the PFMS for correction by the subdistrict office and re-routing to the bank.[14]

District officials have supervisory positions at the top of the MGNREGS administrative hierarchy. They call, text, and meet with subdistrict officers in person and through video meetings to discuss program performance and issues such as payment processing delays. The district CEO oversees general district administration, whereas the district PO solely focuses on MGNREGS and reports to the CEO. In our baseline surveys, the district POs in our study states ranked different dimensions of MGNREGS implementation in order of importance for assessment of subdistrict MGNREGS performance.[15] Figure 1a shows that worker payment delays received the highest average rank out of six categories, followed

[12] These are the official titles in Madhya Pradesh. The corresponding titles in Jharkhand are Assistant Program Officer (PO) and Development Commissioner (CEO).

[13] Subdistrict POs routinely visit GPs and, in turn, frontline agents regularly travel to subdistrict offices for coordination purposes. They also communicate using WhatsApp groups.

[14] The majority of rejections relate to invalid recipient account, bank, or individual identification (Aadhaar) numbers, or accounts being "frozen" due to limited use.

[15] Section 3.1 describes the baseline surveys in more detail.

closely by work provision.

District and subdistrict officials use various performance incentives with subordinates, such as posting transfers, "show cause notices" that formally require an explanation of poor performance, suspensions, and salary withholding. At baseline, 68 percent of district officials indicated having transferred subdistrict subordinates for performance reasons.

2.2 Challenges in MGNREGS implementation

The federal government mandates that, following a six-day work cycle, Stage 1 of worker payment processing should be completed within a maximum of eight days. Based on data for the universe of 3.1 million attendance registers in our two study states for the year prior to the PayDash intervention (February 2016 through January 2017), the subdistrict-month average processing time over this range was 18 days.[16]Appendix Figure A2 shows additionally that more than 85 percent of subdistrict-months exceeded the eight-day threshold, with a long right tail to the distribution.

Delays may arise at the GP level while subdistrict officials await engineers to measure worksite progress and other frontline agents to digitize worksite and attendance data. Delays can occur at the subdistrict level when officials are slow in verifying submitted attendance register and work progress information or signing off on payment requests. Greater time taken to complete Stage 1 is typically reflected in greater time taken for workers to receive wages in their accounts; the sudistrict-level correlation between Stage 1 and overall processing times, averaged over the year preceding the intervention, is 0.82. When asked at baseline to identify the most important challenges faced by MGNREGS participants, both subdistrict officials and district POs ranked payment delays second highest on average out of seven categories, behind only low program wage rates (Appendix Figure A3).

Turning to work provision, slow payment processing can limit citizen demand for the program. In addition, the inability of the program to meet household demand for timely work is frequently noted in policy and news reports. For example, Azim Premji University (2022) find, based on survey data collected across four states including Madhya Pradesh, that 48 percent of households (37 percent in Madhya Pradesh only) were never able to access as much

[16]Payment delays in MGNREGS undermine the protective premise of the program (Basu and Sen 2015; Muralidharan et al. 2018), leading workers to rely on alternative, largely negative, coping strategies which increase their vulnerability to exploitation (Dréze 2020).

work through the program as desired during the 2019-20 fiscal year. The most commonly cited constraint to work access reported by citizens was a lack of available worksites. The number of active worksites and public awareness of available work opportunities reflect, in part, choices made by local and mid-level officials.

In our baseline survey, subdistrict officials identified the most important MGNREGS challenges they faced as administrators. Figure 1b shows the highest average rank out of eight categories went to "infrastructural issues such as poor internet connectivity and power shortages". Officers also viewed low demand for MGNREGS work as a significant issue, ranking "inadequate demand registration due to factors such as low motivation and payment delays" second highest on average.

Officer emphasis on internet connectivity is consistent with our findings in more detailed semi-structured interviews with officials conducted at the intervention design stage. They emphasized there the importance of using administrative data available on the central government MGNREGS website for monitoring work verification and payment processing, but also stated that doing so was very time consuming.[17] This is understandable since, to view information on these steps, officials need to visit separate webpages for each GP-by-processing-step – in a setting where, for example, subdistrict officials manage more than 50 GPs on average and the government officially subdivides Stage 1 into five different steps. Additional effort is then required to export and put this information into formats better suited for officers' needs. These observations informed the design of the Paydash platform, which we describe in Section 2.4.

2.3 Conceptual framework

As described in Section 2.1, MGNREGS work verification and payment processing occurs within a multi-tiered bureaucratic hierarchy. District officers manage and monitor the performance of subordinate district officials. These subdistrict officers complete the later verification and processing steps themselves and in turn manage and monitor local-level officials, who are responsible for carrying out the earlier steps.

Both district and subdistrict officers must exert costly effort in gathering the information necessary to identify delays, determine who to hold accountable, and take action to address problems. We assume that officers may be influenced by factors including extrinsic perfor-

[17] In Section 3.2, we provide evidence that MGNREGS officials in general face high workloads.

mance incentives and intrinsic motivation. In this setting, a technology that reduces the costs of information acquisition has the potential to reduce payment processing times when provided at either the district (upper) or subdistrict (middle) level.

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

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

The impacts of PayDash on other dimensions of MGNREGS performance are also ambiguous. By incentivizing or otherwise causing (e.g., increasing salience) officers to allocate greater effort to payment processing, the amount of effort put toward other parts of program administration could be reduced, leading outcomes in those domains to worsen – i.e., multitasking concerns may be relevant. Alternatively, by making it easier for officials to gather information and to communicate with and manage subordinates, PayDash could free up officer bandwidth to put toward other aspects of program performance, resulting in improvements in those areas. In addition, even if information constraints are broadly relevant across different regions, the impacts of PayDash may differ depending on the content of the information it makes easier to acquire. If, e.g., areas where middle managers oversee a larger number of local administrative units have slower processing times, gains in program performance may be stronger in that dimension in those locations as compared to areas with a lower ratio of local agents to middle managers.

2.4 The PayDash platform

We developed "PayDash", an Android smartphone and web-based application designed to provide easy access to actionable information on MGNREGS work verification and payment processing, with India's central Ministry of Rural Development (MoRD). Timestamps from officials logging into the MGNREGS MIS and completing work verification and payment processing for each attendance register underpin PayDash. The MIS sends this information to PayDash using web application programming interfaces (APIs), with the auto-generation of the timestamps eliminating user-provided information accuracy concerns (Muralidharan et al. 2021). Logins are user-specific, so officers receive daily-updated data solely for their jurisdiction. The PayDash mobile app is offline compatible, allowing information from the last time of update to be viewed even in areas with poor internet and mobile connectivity.

PayDash considers attendance registers as the unit for officer action, and is customized by level of administrative hierarchy. The left panel of Appendix Figure A4 displays the subdistrict PayDash user's homescreen. This panel displays daily statistics on delayed attendance registers for all GPs in the subdistrict, allowing officers to access specific cards. Each card – a screen corresponding to a specific GP and frontline agent – displays the number of attendance registers delayed at steps for which that individual is responsible, and details about each delayed attendance register (see right panel of Appendix Figure A4). To communicate downward in the hierarchy, the user can click an icon on this card to call or WhatsApp the subordinate with attendance register details. PayDash also has a performance dashboard that displays charts of subdistrict and GP-wise current and historical processing time, both overall and by step (see Appendix Figure A5).

District PayDash is structured similarly to the subdistrict version, but provides less granular information. Home screens display district-level statistics, and their cards correspond to subdistricts. Each card lists the the total attendance registers delayed and by step, and contact icons for the relevant mid-level official. The performance dashboard is structured identically to that in the subdistrict version, but provides information at the district and subdistrict levels.

2.5 Intervention design and implementation

We randomized access to PayDash across the entirety of the states of Madhya Pradesh and Jharkhand, covering 73 districts and 561 subdistricts.[18] Districts were randomly assigned into the following groups: 17 districts where district administrators received PayDash ("District Only"); 16 districts where subdistrict officials received Paydash ("Subdistrict Only"); 20 districts where both district and subdistrict administrators received PayDash ("Combination"), and 20 districts forming our control with no Paydash provided.[19] Within each treated level of the administrative hierarchy, PayDash was provided to the CEO and PO.[20] Subdistrict access to PayDash was clustered by district due to the high potential for within-district spillovers – e.g., it is common for district officials to hold regular district-wide video conference meetings with subdistrict officials to discuss MGNREGS performance.

We rolled out PayDash across Madhya Pradesh in February and March 2017 and Jharkhand in October 2017 in collaboration with each state's MGNREGS department. In the subsequent analysis, all districts in Madhya Pradesh are assigned a February rollout month. The intervention period continued through August 2018.[21] Our geographically spread training sessions allowed us to train and survey district and subdistrict MGNREGS personnel in person. A total of 1,293 district and subdistrict CEOs and POs (94% of all positions) attended 177 in-person training sessions. Officers unable to attend the initial sessions were later followed up with individually for training.

Training sessions for control and treated districts were conducted separately, as were sessions for subdistrict and district officials. All officials, regardless of treatment assignment, received "refresher" training on MGNREGS MIS tools to ensure they could access MIS information. Treatment assignment therefore varied how easily officers could access payment-related information, not whether they knew how to acquire it or had more MGNREGS system knowledge. Training sessions for treated officials additionally involved installing the PayDash

[18]This set excludes one pilot district in each state.

[19]We assigned treatments in approximately equal proportions across Madhya Pradesh's 50 study districts. In Jharkhand's 23 study districts, we assigned approximately one-third to control and Combination, and one-sixth to District Only and Subdistrict Only. In each state, we stratified by above/below median values of average muster-roll-by-worker payment time and average per-subdistrict volume of person-days within the April 2015 to June 2016 range. Appendix Section B.2 provides additional details on these variables.

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

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

mobile-phone app and instruction in how to use the platform. PayDash training typically took an hour.[22]

Throughout the intervention, we contacted each district at multiple points to identify position changes and adjust PayDash access.[23] New officers in treatment areas were trained and provided PayDash access. Officers transferred between treated areas had their PayDash region-specific information updated, while those exiting treated areas had their login access deactivated.

3 Data and Empirical Strategy

3.1 Data sources

For our analysis, we draw upon multiple sources of administrative data, automatically captured data on PayDash usage, and data collected directly from MGNREGS officials.

PayDash usage data Using Google Analytics data on user engagement with PayDash during the intervention period, we generate officer-month-level measures of the total number of user sessions, duration of usage (available only for the mobile application), and number of WhatsApp messages and calls placed from within the mobile application.[24] The total session and mobile duration measures provide lower bounds because the Google Analytics data does not capture user engagement when PayDash is in offline mode.

Officer survey data Conditional on being present at a training session, over 99 percent of officers completed a baseline survey.[25] The information collected in our baseline surveys of district and subdistrict CEOs and POs in Jharkhand and Madhya Pradesh includes sociodemographic characteristics and details of the work environment, management practices, and MGNREGS administration. Surveys were completed in person prior to the MGNREGS and PayDash training sessions. Between May and December of 2020, we conducted a follow-

[22] Appendix Section B.1 provides additional training session details.

[23] In this period, the states did not centrally maintain regularly updated rosters of officials' postings.

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

[25] The training coverage gap was due primarily to vacant positions at baseline - i.e., the previous officer had vacated the position and a replacement had not yet been posted. Training participation and baseline survey completion do not differ significantly with treatment for either district or block officer positions.

up survey with the set of baseline subdistrict and district POs in Madhya Pradesh. We achieved a coverage rate of 77.1 percent for these 358 officers, with the single-state focus and lower completion rate compared to baseline largely reflecting challenges of conducting phone-based surveys with officers while they managed the government response to COVID-19.[26] These surveys collected additional information on management practices, MGNREGS administration, and treated officials' use and perceptions of PayDash.

MGNREGS administrative data We obtained data on worker payment processing for the universe of approximately 19.5 million attendance registers (muster rolls) issued in Jharkhand and Madhya Pradesh between February 2016 and August 2018. For each attendance register, we observe the GP in which it was issued, the start and end date of the associated workspell, and the date of associated payment request submission by the subdistrict office to the central funds management system (PFMS). These data allow us to determine the length of time taken to complete the work verification and payment processing steps for each attendance register. We use this information to construct processing-time-based measures and the total number of attendance registers at the subdistrict-month level.

Separate administrative data sources covering the same time period allow us to construct subdistrict-month-level measures of the total person-days worked by MGNREGS participants, the number of active worksites, and the average share of payment requests subsequently rejected at the PFMS stage.[27] We also incorporate data on the characteristics of all MGNREGS participants in our study states over this period – drawn from publicly-available worker identity documentation – to construct subdistrict-month measures of the number of participating households and the average number of days worked per household. To consider the composition of program participants, we generate the shares of workers belonging to marginalized groups, specifically females and members of government-identified "Below Poverty Line" households.

External audits data We acquired publicly available data produced as part of "social audits", GP-level exercises conducted by independent government auditors external to communities to assess local MGNREGS delivery in a variety of dimensions. Audits are assigned to GPs on a rotating basis and conducted over the course of approximately one week in a

[26]The survey completion rate does not differ significantly by treatment for either district or block officers.
[27]Section 4.3 discusses the PFMS stage in greater detail.

given GP.[28] Approximately 70 percent of GPs experienced an audit covering some range of the intervention period, with no GP receiving more than one such audit and the likelihood balanced across treatment arms. We use data from the audits to construct measures of the quality of MGNREGS implementation and incidence of corruption, as well as a measure of community demand for work through the program.

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

3.2 Summary statistics and balance

In Tables A1 and A2, we use our administrative and baseline survey data to examine and test for balance in administrative and officer characteristics. Column (1) reports means and standard deviations for control districts, and columns (2) through (4) present the coefficients and standard errors from regressions of each characteristic on PayDash treatment arm indicators (with control as the omitted category), controlling for randomization strata. Column (5) reports p-values from tests of the joint hypothesis of zero-valued treatment arm coefficients. We observe that treatment assignment is well balanced.[29]

We first consider a set of district-level administrative and program characteristics in Panel A of Table A1. The average district in our study states is made up of 7.7 subdistricts and has an average of 57 GPs per subdistrict, with a large amount of variation in the latter. Average population as reported in the 2011 census is approximately 1.4 million, with 77 percent of residents living in rural areas. We then consider MGNREGS-related variables, defined over the year prior to the launch of the intervention (February 2016 through January 2017). District-level average processing time is 19 days, with an average absolute deviation

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

[29] Of 177 pairwise differences considered in Tables A1 and A2, one is significant below the 1 percent level, six are significant below the 5 percent level, and 25 below the 10 percent level. Out of 59 joint tests, the null is rejected twice below the 5 percent level and three times below the 10 percent level.

from the median of 10.4 days. More than 2.3 million person days were worked across 42,000 attendance registers per district on average, and the average share of payment requests subsequently rejected at the PFMS stage is 9 percent.[30]

In Panels B and C, we consider baseline sociodemographic and work-related characteristics of MGNREGS officers at the district and subdistrict levels, respectively.[31] Officers at both levels are typically mid-career (aged early 40s), and predominantly male and educated beyond the college level. Smartphone ownership is nearly universal (not shown) and more than 90 percent of officers reported that they access online MGNREGS administrative data via the status quo interface at least once a day.[32]

High workloads are pervasive for MGNREGS officials. Officers at both administrative levels indicate working 70 or more hours per week and making 40 or more work-related calls per day on average, with higher reports at the subdistrict level. It is also not uncommon for officials to cover temporarily for vacancies in other positions, with 44 percent of district officers and 30 percent of subdistrict officers having an “additional charge” at baseline. Consistent with bandwidth constraints to information acquisition due to work overload, when asked what the average time taken for MGNREGS worker payment delivery in their jurisdictions was over the previous year, the average absolute deviation between the value given by officers and the actual value as a share of the actual value (“knowledge gap”) was 38 percent for district officials and 45 percent for subdistrict officials. In addition, subdistrict officials on average report being in regular weekly contact with local agents in only 37 percent of the GPs under their purview. Finally, 93 percent of district officials themselves indicate that subdistrict officials are overworked (not shown). For use in our subsequent analysis, we generate a “workload” index variable based on hours worked per week, calls per work day, having an additional charge, knowledge gap, and (for subdistrict officials) irregular local agent contact variables.[33]

[30] Appendix Table A2 further considers the district-level average monthly numbers of working households and days worked per household.

[31] We pool CEOs and POs at each level, and the underlying officer-level regressions for these panels additionally include a program officer indicator. Differences in sample sizes across characteristics reflect variation in question-specific response rates.

[32] At the district level, this variable is only available for POs.

[33] We construct this index separately by officer type, calculating z-scores for each component variable and defining the index value as the average of the component z-scores.

3.3 Empirical approach

To estimate the impacts of randomly providing PayDash at different levels of the MGNREGS administrative hierarchy, our primary specification for analysis using panel data is:

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

where s is a subdistrict in district d in month t, α_s and α_t are subdistrict- and month-level fixed effects, and Y_{sdt} is an outcome of interest.[34] TD_{dt}, TS_{dt}, and TC_{dt} are indicator variables for district-level access to District Only PayDash, Subdistrict Only PayDash, and Combination PayDash, respectively. Also included are controls for district-specific linear time trends, θ_{dt}, to adjust for any chance occurrence of differential pre-trends. Standard errors are clustered by district. We use this design to evaluate and compare the impacts of district- and subdistrict-level provision of PayDash, as well as to test for complementarity or substitutability between them (against $H_0 : \beta_3 = \beta_1 + \beta_2$). We also estimate a version of Equation (1) with the treatment-arm-specific indicators replaced by a single indicator for any PayDash provision. For corresponding analysis of the impacts of PayDash using cross-sectional data, our primary specification involves regressing the outcome of interest on treatment indicators and randomization strata fixed effects, clustering standard errors at the district level.[35]

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

$$Y_{sdt} = \sum_{\substack{-5 \leq \tau \leq 8, \\ \tau \neq -1}} [\beta_{1,\tau} TD_{\tau,dt} + \beta_{2,\tau} TS_{\tau,dt} + \beta_{3,\tau} TC_{\tau,dt}] + \alpha_s + \alpha_t + \theta_{dt} + \varepsilon_{sdt}, \tag{2}$$

where $TD_{\tau,dt}$ is an indicator variable for whether month t in district d falls τ months relative to District Only PayDash provision. The month prior to PayDash provision ($\tau = -1$) is omitted as a normalization, $\tau = -5$ captures all periods five or more months prior to rollout, and $\tau = 8$ captures all periods eight or more months after rollout.[36] $TS_{\tau,dt}$ and $TC_{\tau,dt}$ are analogous relative-period-specific indicators for Subdistrict Only and Combination PayDash

[34]Randomization strata are absorbed by the subdistrict fixed effects.

[35]We describe any context-specific adjustments to this approach at the relevant points in the text.

[36]The sample period begins in July 2016, the first month after the range used to generate the randomization strata.

provision, respectively.[37] To examine potential heterogeneity in the effects of PayDash by districts' administrative structure, we use specifications analogous to equations (1) and (2) that allow the impacts of each treatment arm to vary by whether a district has an above- versus below-median average number of GPs per subdistrict.[38] We also consider a more flexible specification where we allow treatment effects to differ by sextile of the average-GPs-per-subdistrict distribution.

4 MGNREGS Performance and Administration Impacts

In Section 4.1, we examine PayDash usage by officer type. Next, using the experimental variation in PayDash access, we identify in Section 4.2 impacts on MGNREGS program performance and assess in Section 4.3 whether officer work quality or corruption were affected. Section 4.4 considers effects on the transfers of mid-level officials.

4.1 Officer PayDash usage

Table 1 presents PayDash usage statistics for subdistrict and district officers. Observations are defined at the locality-month level for each officer level, covering the set of intervention months in our two experimental states. The means and standard deviations of monthly usage are calculated for total PO and CEO usage at each officer level, restricting to localities where only officers at the listed level of the hierarchy received PayDash. As mentioned before, our data provides lower bounds on usage because it does not capture when officers use PayDash in offline mode.

We observe that average usage is similar at the district and subdistrict levels, at roughly 4 to 5 sessions and 25 to 30 minutes of mobile-based engagement per month. Appendix Table A3 shows that nearly all PayDash engagement occcurs with the POs at each level, which is unsurprising since POs are solely tasked with the management of MGNREGS, while CEOs have a wider range of responsibilities. In addition, breaking the number of PayDash sessions out by interface type (not shown), fewer than five percent of sessions for each officer type occur through the web-based interface, suggesting value to officials of the mobile-tailored

[37] Given our staggered treatment timing, the corresponding interaction weighted estimator (Sun and Abraham 2021) is used in Appendix Figure A10.

[38] We additionally examine robustness to the inclusion of interacted controls.

presentation and offline availability of information in the PayDash Android application.

In columns (3) and (6) of Table 1, we consider the number of calls made and WhatsApp messages sent to subordinate officials using the in-app contact feature. Use of this functionality is concentrated at the district level, likely reflecting in part that a greater share of their supervision of and information sharing with subdistrict subordinates occurs remotely as compared to subdistrict officials in relation to their GP-level subordinates.

We next use the random variation in which levels of the bureaucracy in each district receive PayDash to determine whether officers' engagement with the platform at a given level is influenced by access at the other level of the administrative hierarchy. For each outcome and officer level, Table 1 also reports the estimated coefficient on an indicator for PayDash provision at both levels of the officer hierarchy, from regressions where the sample is all locality-months for which officers at a given level received PayDash and which also include month and strata fixed effects. The usage differences for subdistrict officials across treatment arms are small in magnitude. While noisily estimated, the results in columns (4) through (6) suggest district officials use PayDash less when their subdistrict subordinates also have access to the platform. Such declines are consistent with a setting where district officials use PayDash to share information with subdistrict officials, a practice that diminishes when those subordinates have direct access themselves. Section 5.3 discusses additional evidence related to information sharing across officer levels.

4.2 Effects on program performance

We next consider the effects of PayDash on outcomes related to payment processing as well as another important dimension of MGNREGS performance, the volume of work completed by rural households through the program. For expositional clarity, we first discuss impacts when the District Only, Subdistrict Only, and Combination PayDash treatment arms are combined into an "Any PayDash" category and then consider the effects of the different treatment arms in relation to one another.

Column (1) of Table 2 shows that PayDash access reduces attendance register processing times by an average of 1.4 days, or 11 percent of the control pre-intervention mean. We consider the dynamics of the effects of PayDash on average processing speed in Figure 2, which plots the relative-month-specific estimated coefficients and 95 percent confidence intervals for the pooled Any PayDash treatment, based on the corresponding version of equation (2).

Reductions in processing times appear a few months after the start of the intervention and persist throughout the evaluation period.[39] As maintaining an average processing time below the eight day maximum mandated by the government is a key performance metric by which subdistrict officers are evaluated, we next examine the impact of PayDash on the likelihood that work verification and payment processing are on average completed "late", i.e., after more than eight days, in a given subdistrict-month. Column (3) of Table 2 shows a 7.1 percentage point reduction in this probability.

To better understand what underlies these improvements in processing performance – e.g., are gains achieved through reductions only in severe delays versus quicker processing more broadly? – we consider the share of attendance registers in each subdistrict-month within different processing time ranges. Figure 3 shows that PayDash leads to a general leftward shift in the distribution of processing times, with significant reductions in the share of attendance registers in each of the bins capturing ranges above 8 days.[40] In addition, as both the average and variability of processing times are relevant to MGNREGS' protective value for low-income rural households, we examine in column (5) of Table 2 the impacts of PayDash on the average absolute deviation from the subdistrict-month median, finding a reduction in variability of 0.52 days (8 percent).

These improvements in payment processing times could come at the expense of reduced processing volume. In column (7), however, we observe an average 20 percent (18.6 log point) increase in the number of attendance registers being generated and subsequently processed. To determine the extent to which this impact reflects an increase in volume of payments processed versus simply the spreading of processing out across a larger number of attendance registers, we consider the log of person-days worked by MGNREGS participants as an outcome. Column (1) of Table 3 shows that PayDash provision results in an average 19 percent (17.2 log point) increase in person-days worked, in a context where more than 170 million workdays were completed in our experimental states over the year prior to the start of the intervention.[41]

Using additional administrative data, we decompose the effect on volume of MGNREGS

[39] Similar dynamics are observed in the lower panels of Figure 2 for the other primary outcomes examined in this section, and in Appendix Figure A8 when each PayDash treatment arm is considered separately.

[40] Appendix Figure A9 presents the estimated effects separately by treatment arm.

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

person-days completed into intensive and extensive margin changes in program participation. Column (3) of Table 3 shows a positive impact of PayDash on the log monthly person-days completed per participating household, explaining half the change in total person-days worked. We thus see in column (5) an increase in log participating households of the same size, though more noisily estimated.[42] In sum, PayDash not only improved payment processing times but also led to an increase in the volume of work completed by, and hence subsequent benefits processed for, MGNREGS participants. In Section 5.1, we present analysis relevant to understanding the extent to which the work volume impacts reflect changes in bureaucratic effort versus public demand.

Finally, we consider how the effects of PayDash on payment processing times and log person-days worked vary by whether the platform was randomly assigned to district versus subdistrict officers and to one versus multiple levels of the bureaucratic hierarchy. As shown in column (2) of Tables 2 and 3, for both processing time and person-days worked, PayDash yields significant improvement when provided at either the district or subsdistrict level. In addition, demonstrating impact substitutability in platform access at the district and subdistrict levels, the effect of providing PayDash to both district and subdistrict officers (β_3) is significantly smaller than the sum of the district only (β_1) and subdistrict only (β_2) effects for both average processing time ($p = 0.041$) and log person-days worked ($p = 0.006$). Furthermore, for neither outcome do we see evidence that the impact of providing PayDash to both district and subdistrict officers is larger than the impact of doing so to either single level of the hierarchy alone.

Interpreted through our conceptual framework, these results suggest first that the gains from PayDash are not driven entirely by strengthening the performance incentives of subdistrict officers via improved district-level monitoring. If this were the case, we would not expect providing PayDash to subdistrict officers alone, which leaves the monitoring technology of district officers unchanged, to yield improvements in program performance. Information constraints at both the upper and middle levels of the bureaucratic hierarchy therefore appear relevant in this context. Second, the substitutability of district and subdistrict PayDash is consistent with treated district officers sharing information with subdistrict officials, leading to redundancy in at least some of the information gains when both levels are treated. In

[42] Appendix Table A4 shows that PayDash also increases the share of workers in the below poverty line category by 0.3 percentage points (2 percent), with no impact on the share female.

Sections 5.2 through 5.4, we provide additional evidence related to these mechanisms.

4.3 Did PayDash influence bureaucrat work quality?

PayDash reduced wage payment processing time while increasing the volume of benefits delivered through MGNREGS, but these improvements could be accompanied by a worsening of bureaucrat work quality. PayDash could worsen the quality of the data officers upload and inspect by increasing pressure to reduce processing times and causing them to put more emphasis on pushing data through the system quickly versus data accuracy. In addition, by making it easier for subdistrict officers to monitor local activities or by relieving bandwidth constraints that free up time, PayDash could increase the ability of these officials to extract rents from lower-level officials or workers in exchange for completing the later steps of payment processing, influencing the nature of corruption.

As a first measure of officer work quality, we consider the probability that worker payment requests are rejected when submitted to the central PFMS following the completion of the Stage 1 steps for an attendance register. At this second stage, the most common reasons a payment is rejected relate to invalid recipient account, bank, or individual identification (Aadhaar) numbers having been entered. These details may be invalid due to data entry mistakes by local bureaucrats; workers providing incorrect information; bank accounts being dormant, closed, or frozen; or errors in the link between Aadhaar and bank accounts.[43] If GP or subdistrict officials are less careful in gathering, entering, or verifying such details in areas with access to PayDash, downstream payment request rejection rates could increase. Alternatively, if PayDash frees up more time for officers to work on such issues or makes it easier to monitor and coordinate with subordinates collecting the relevant details, rejection rates may decrease.

At the PFMS stage, worker payment requests from multiple attendance registers are typically grouped into a single "wagelist". We observe the share of these payment requests rejected for each wagelist and average the rejection rate across wagelists in each subdistrict-month. Using the same panel empirical approach as above, we find no evidence of a negative quality impact as captured by payment request rejection. Columns (1) and (2) of Table 4

[43] In these cases, the subdistrict office can attempt to address the issue and re-submit the payment request. In practice, gathering necessary information to address rejections is time consuming, requiring coordination with local-level officials and potentially leading to additional delays in payment processing or failure to correct the reason for rejection at all.

show that providing PayDash access to officers if anything can reduce the average share of payment requests rejected.

Our second measure of quality is based on official reports from over twenty thousand independently implemented, GP-level audits of MGNREGS implementation covering our intervention period. Our outcome of interest is an audit-level irregularity index based on the occurrence of issues in each of the four main categories considered in the official audit reports: financial deviation (typically linked to poor record keeping; reported in 12 percent of control locations), financial misappropriation (including bribes, paying ghost workers, or other evidence of graft; reported in 10 percent of control areas), grievances raised (related to access to work, wages, etc.; reported in 14 percent of control areas), and other process violations (reported in 19 percent of control locations).[44] This aggregate measure therefore captures dimensions of both work quality and potential corruption.

We regress the irregularity index measure on district-level treatment indicators and strata fixed effects, clustering standard errors at the district level.[45] Columns (3) and (4) of Table 4 show no evidence of PayDash impacts. Appendix Table A6 also shows no effects when we consider each of the four index components separately. Overall, these results demonstrate that providing PayDash access to MGNREGS officials did not result in deterioration of their work quality or worsening of corrupt behavior as captured by payment request rejections and the external audit process.

4.4 Impacts on officer posting transfers

In bureaucratic systems where the use of financial incentives is often circumscribed, allocation to specific postings may be used as either punishment or reward (Finan et al. 2017; Khan et al. 2019). Such transfers can be both costly to implement and serve as a blunt tool for attempting to improve overall performance. In this section, we examine whether access to PayDash influences the probability that subdistrict officials are transferred, relying on the novel data we collected via calling rounds to district offices.

Transfers are common in our study context, with 45 percent of subdistrict officers in control areas having been transferred within six months of intervention roll-out in each state.[46]

[44] The index is constructed as the average of z-scores generated for each component.

[45] The sample excludes the 8 percent of GPs with fully pre-intervention audit reference ranges.

[46] The large majority (89 percent) of subdistrict officer transfers during the study time frame occurred within the same district.

In the final two columns of Table 4, we examine whether PayDash affected the likelihood that subdistrict officers were transferred within this time range. The underlying regressions are at the subdistrict-position level and include treatment indicators together with strata fixed effects and a PO indicator. Standard errors are clustered at the district level. Column (6) shows that providing PayDash to district officers alone reduced the probability of transfer at the subdistrict level by 10.6 percentage points (23.7 percent), statistically indistinguishable from and similar in magnitude to the effect when both district and subdistrict officials receive PayDash.[47] In contrast, the estimated impact of only subdistrict officials receiving platform access is positive, small in magnitude, and statistically distinguishable from those of the other two treatment arms.[48] Extending the range of consideration to 17 months – the maximum available in our data, and only for Madhya Pradesh due to its earlier PayDash rollout – we see a similar pattern in Table A5, with PayDash reducing subdistrict officer transfers only when district officers are among those given access.

The reduced movement of subdistrict officers in areas where district officials receive PayDash is consistent with some combination of district principals becoming more informed about subdistrict middle-manager performance and their responding to treatment-driven changes in that performance. The fact that the MGNREGS performance improvements shown in Section 4.2 are present for the Subdistrict Only treatment arm while the subdistrict officer transfer impacts are absent, however, indicates that the effects on transfers from district-level PayDash are at least partially driven by changes in district officials' informedness. Regardless of the relative importance of the underlying channels, inasmuch as transfers are a costly tool to manage subordinates, these results suggest that reducing principals' information costs could have important implications for broader bureaucratic efficiency.

5 Evidence on Mechanisms

We first consider in Section 5.1 the relevance of changes in rural household demand and officer effort to the observed PayDash-driven increases in MGNREGS worker participation. Following this, we provide a combination of evidence suggesting that reducing the severity of constraints to information acquisition for middle managers is an important channel

[47] $p = 0.505$

[48] Comparisons to District Only PayDash and Combination PayDash yield $p = 0.012$ and 0.060, respectively.

through which PayDash improves MGNREGS performance. In Section 5.2, we test for impacts of PayDash on subdistrict officer knowledge and examine the value officers place on the information provided by the platform. Section 5.3 considers officials' own perceptions of information acquisition from PayDash and how they used this information. Finally, in Section 5.4, we examine how the effects of PayDash on MGNREGS performance are mediated by administrative structure and associated variation in middle manager workload.

5.1 Household work volume: public demand and bureaucrat effort

As discussed above, the volume of person-days worked by MGNREGS participants is a function of factors including bureaucrat effort and rural household demand. In this section, we consider the extent to which the earlier observed increase in household work volume caused by PayDash is due to greater demand for work from rural communities and increased effort toward work provision by MGNREGS officials.

First, we test whether PayDash influenced community demand for MGNREGS work using information captured in the external audits, where auditors report whether they observed "some" or "a lot of" unmet demand (versus "none") based on responses given during door-to-door visits to households in each GP.[49] To assess the effect of PayDash, we regress an indicator for unmet community work demand on treatment indicators and strata fixed effects, clustering standard errors at the district level. Columns (1) and (2) of Table 5 shows that the likelihood of unmet community demand for MGNREGS work is greater in areas with PayDash.

Next, given the key role that subdistrict officials play in initiating MGNREGS projects at different worksites, we consider as an outcome the log number of active worksites. Columns (3) and (4) show that the provision of PayDash to MGNREGS officials leads to a rise in worksites. These results suggest that greater community demand and bureaucrat effort both played roles in the observed increase in person-days worked, where the former could occur for reasons including improvements in program implementation quality such as quicker payment processing increasing rural households' perceived value of program participation and MGNREGS officials more strongly publicizing the availability of projects.

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

5.2 Officer information acquisition

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

As a proxy for general officer informedness, we use our follow-up survey data to generate a "knowledge gap" measure analogous to that defined in Section 3.2.[50] We then regress this measure for subdistrict POs on treatment indicators and strata fixed effects, clustering standard errors at the district level.[51] Columns (5) and (6) of Table 5 show that PayDash improves the accuracy of officers' responses, reducing the knowledge gap by roughly 7.8 percentage points (19 percent), with statistically indistinguishable effects of similar magnitude across treatment arms. In addition, we observe suggestive evidence of substitutability in the impacts of district and subdistrict PayDash on subdistrict officer knowledge.[52] Together with the earlier identified substitutability in impacts on MGNREGS program performance, this finding is consistent with a setting where district officials share management-relevant information from PayDash with their subdistrict subordinates. These results could, however, also reflect that subdistrict officers' knowledge improves under district-level PayDash access because strengthened monitoring leads them to increase their information gathering effort, ultimately improving program performance. In the next section, we utilize officers' self-reports on how they used PayDash to consider both these possibilities.

To consider the extent to which officers value the information being provided through PayDash, we next take advantage of an exogenous temporary shock to the platform's functionality. For the majority of July 2017, a central government server outage caused the API underlying PayDash to become inoperative. As a result, during this outage period the platform no longer provided up-to-date information on delayed attendance registers or summary statistics on processing time performance. The in-app contact features, however, remained

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

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

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

functional. In Table 6, we show that usage of PayDash by both district and subdistrict officers declined significantly in the month of the outage, consistent with officers valuing the information provision aspect of the platform.[53]

5.3 Bureaucrat self-reports on PayDash

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

Figure 4 shows that 81 percent of district officials and 60 percent of subdistrict officials who received PayDash indicate that the platform made it easier for them to acquire information about MGNREGS wage payment processing in their jurisdictions. In addition, 19 percent of district officers and 27 percent of subdistrict officials report that PayDash allowed them to acquire information they did not previously have.[54] While, as discussed previously, officers can technically generate the information provided in PayDash using data available through existing government websites, accessing and processing this data so it would be more useful for day-to-day decision making is a time intensive process that may be practically infeasible to do regularly. Beyond easing information constraints, PayDash was reported to function as a reminder to pay more attention to wage payment processing by 31 percent of district officials and 46 percent of subdistrict officials, potentially leading them to allocate more effort to that dimension of their duties.

When asked how they used the information from PayDash, 68 percent of district officers and 63 percent of subdistrict officials report sharing it with subordinates working on MGNREGS within their jurisdictions. Reports of using PayDash to evaluate the performance of subordinates are less frequent, though not uncommon, with 25 percent of district officials and 40 percent of subdistrict officers indicating that they did so. These results overall show that, from the perspective of users themselves, PayDash made it easier to acquire management-relevant information, which was both shared with and used to monitor

[53]This analysis is for only Madhya Pradesh, as the outage occurred before PayDash rollout in Jharkhand.
[54]94 (75) percent of district (subdistrict) POs answered affirmatively to either information-related question.

subordinate officials.

5.4 Heterogeneity by administrative structure and workload

Constraints on bureaucrats' managerial capacity may differ based on the administrative structure within which they operate, potentially influencing both baseline MGNREGS performance and the impacts of PayDash. For officials at a given level of the administrative hierarchy, having a larger number of subordinates working at the level below them has the potential benefit of providing more personnel with which to complete a given amount of work. However, being responsible for a greater number of subordinates may exacerbate bandwidth constraints to gathering management-relevant information as well as to supervision more generally. The relationships of the subordinate-to-supervisor ratio to initial program performance and the value of lowering the costs of information acquisition are thus ambiguous, and in this section we empirically examine them in the context of PayDash provision to MGNREGS officials.

The MGNREGS administrative hierarchy in our study states has a large amount of variation in the number of GPs per subdistrict, with less so in the number of subdistricts per district.[55] Given that the experimental variation in PayDash access occurs at the district level and within-district transfers of subdistrict officials are common, we consider heterogeneity in the impacts of PayDash between districts with above- versus below-median average numbers of GPs per subdistrict ("high GP ratio" and "low GP ratio", respectively). Subdistrict officials in high-GP-ratio districts oversee an average of 80 GPs as compared to 32 GPs in low-GP-ratio districts. The GP-to-subdistrict ratio is not randomly determined and so may be associated with other characteristics that mediate the impacts of PayDash on MGNREGS performance. As a robustness check, we therefore estimate specifications where we additionally interact PayDash access with a set of such potential characteristics: having an above-median number of subdistricts, log population, rural population share, and baseline attributes of district and subdistrict program officers.[56]

[55] The means (standard deviations) of GPs per subdistrict and subdistricts per district are 39.4 (27.9) and 7.7 (4.0), respectively. Our review of administrative documents indicates that subdistricts as entities were established in the 1950s, with rarely changing boundaries. New GPs may be established when current local populations exceed values provided through state-specific guidance. No changes of either type occurred during our evaluation period.

[56] Officer attributes are age, being female, and post-graduate completion, averaged by district for subdistrict POs.

Column (1) of Table 7 shows that providing PayDash access leads to a 0.7 day reduction in average processing times in low-GP-ratio districts, as compared to a total drop of 2.6 days in high-GP-ratio districts.[57] Comparing average processing times prior to the intervention, we also see that high-GP-ratio districts (16.8 days) were in general slower to begin with than low-GP-ratio districts (12.2 days). The concentration of PayDash impacts in high-GP-ratio districts holds in columns (2) and (3) as we include interactions with an analogously constructed high subdistricts-per-district indicator and additional controls. Figure 5, where we allow for heterogeneity in the effects of PayDash by sextile of the average-GPs-per-subdistrict distribution, shows a general strengthening in impact as the average GP-to-subdistrict ratio increases.[58]

To better understand the relevance of administrative structure to the effects of PayDash, we examine first whether subdistrict POs' baseline administrative burden as captured by our workload index tends to be larger in high-GP-ratio districts.[59] We observe in Appendix Table A8 a strong positive relationship between subdistrict officer workload and being based in a high-GP-ratio district. When considering district POs, we see no evidence of increased workload in areas where they oversee a larger number of subdistricts, potentially reflecting the smaller range of values in this dimension.

Next, in columns (4) through (6) of Table 7, we allow the impacts of PayDash to vary directly with whether a district is above-median in terms of average value of the subdistrict PO workload index ("high workload"). Column (4) shows that the reductions in payment processing times are limited to high-workload areas. In column (5), where both high-workload and high-GP-ratio interactions are included, we see that the high-workload interaction remains significant and similar in magnitude as compared to column (4), while the high-GP-ratio interaction is smaller in magnitude as compared to column (1) and no longer significant. This pattern is unchanged in column (6) when we further include interactions with high subdistricts-per-district and district-PO-workload indicators and additional controls.[60] Finally, we see in Appendix Table A11 that the earlier identified reductions in

[57] Appendix Table A7 shows impacts separately by PayDash treatment arm, with substitutability in the provision of PayDash again evident.

[58] Appendix Figure A11 shows that the PayDash-driven reductions in shares of attendance registers in each of the bins capturing ranges above 8 days are also driven primarily by changes in high-GP-ratio districts.

[59] We regress officer-level workload on district-level indicators for above-median average GP-to-subdistrict ratio and number of subdistricts. We additionally include a state indicator and cluster standard errors at the district level. Appendix Table A9 considers each of the underlying index components.

[60] Appendix Table A10 shows that these results hold when alternatively using continuous interactions.

the probability of processing being "late" on average and in processing variability caused by PayDash are similarly concentrated in high-workload areas. In contrast, we do not observe such heterogeneity in the impacts of PayDash on the volume of days worked by MGNREGS participants.[61]

Overall, we see that subdistrict officials experience higher workloads on average in areas where they oversee a larger number of local administrative units, and their higher workloads are strongly associated with larger PayDash-driven improvements in payment processing times.[62] These findings provide additional evidence consistent with middle-manager bandwidth constraints to information acquisition and supervision negatively impacting the quality of MGNREGS implementation.

6 Conclusion

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

Provision of PayDash led to improvements in payment processing times and the volume of program benefits delivered, whether made available at the district or subdistrict level. We see strong evidence of substitutability of district and subdistrict PayDash access in impacts on payment processing times and work volume, and a variety of evidence suggesting that this substitutability relates at least in part to upper-level officers sharing information from PayDash to help their subordinates, rather than using it simply to better monitor their performance. These gains in program performance were not accompanied by deterioration

[61]Nor are differences observed in baseline volume of days worked between high- and low-workload areas.

[62]We also observe in Appendix Table A12 that subdistrict POs use PayDash more in high-workload districts.

in an important measure of officer work quality – payment request rejections – or by worsened corruption as captured by independent government audits. Access to PayDash also reduced the occurrence of a potentially costly form of officer performance management, the reallocation of subordinate officials across jurisdictions.

PayDash provided existing information in a more readily accessible and actionable format for bureaucrats. Our results therefore highlight how seemingly small costs of information acquisition for the government officials who administer public programs can be an important constraint to the quality of service delivery in low-income settings. The significant improvements achieved by reducing information access costs manifested in an environment that was already largely digitized, suggesting information constraints are not necessarily resolved simply through technological advancements such as digitization of social protection program data. Practically speaking, our findings also suggest the broader potential of deploying add-on digital tools in social safety net programs, which are now widespread in lower-capacity bureaucratic settings, to reduce information constraints and achieve meaningful improvements in program implementation.

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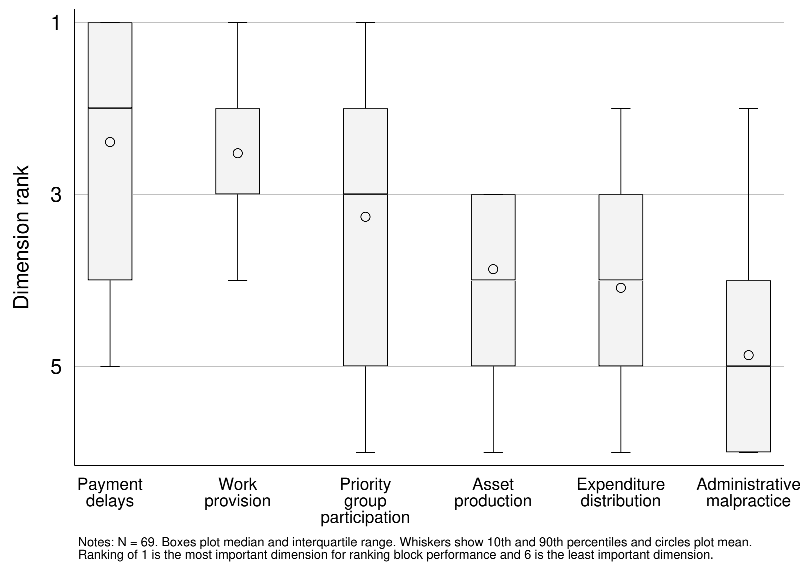
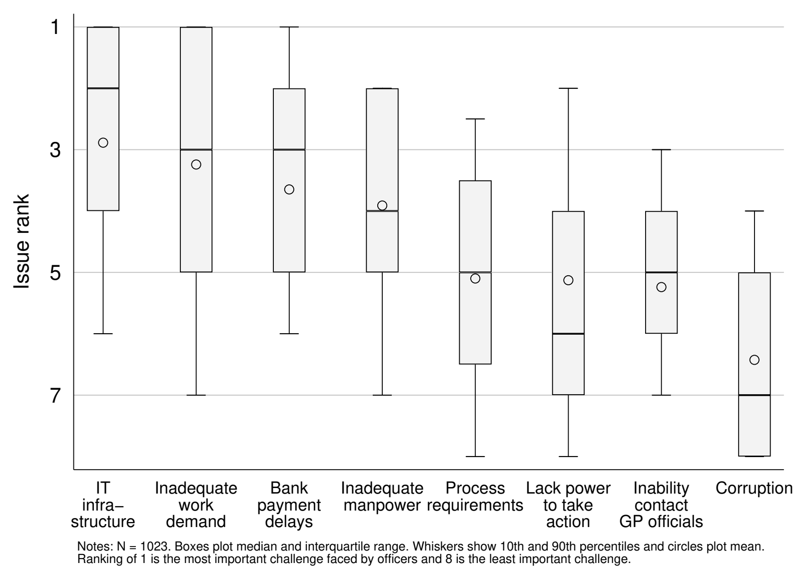
Figures and Tables

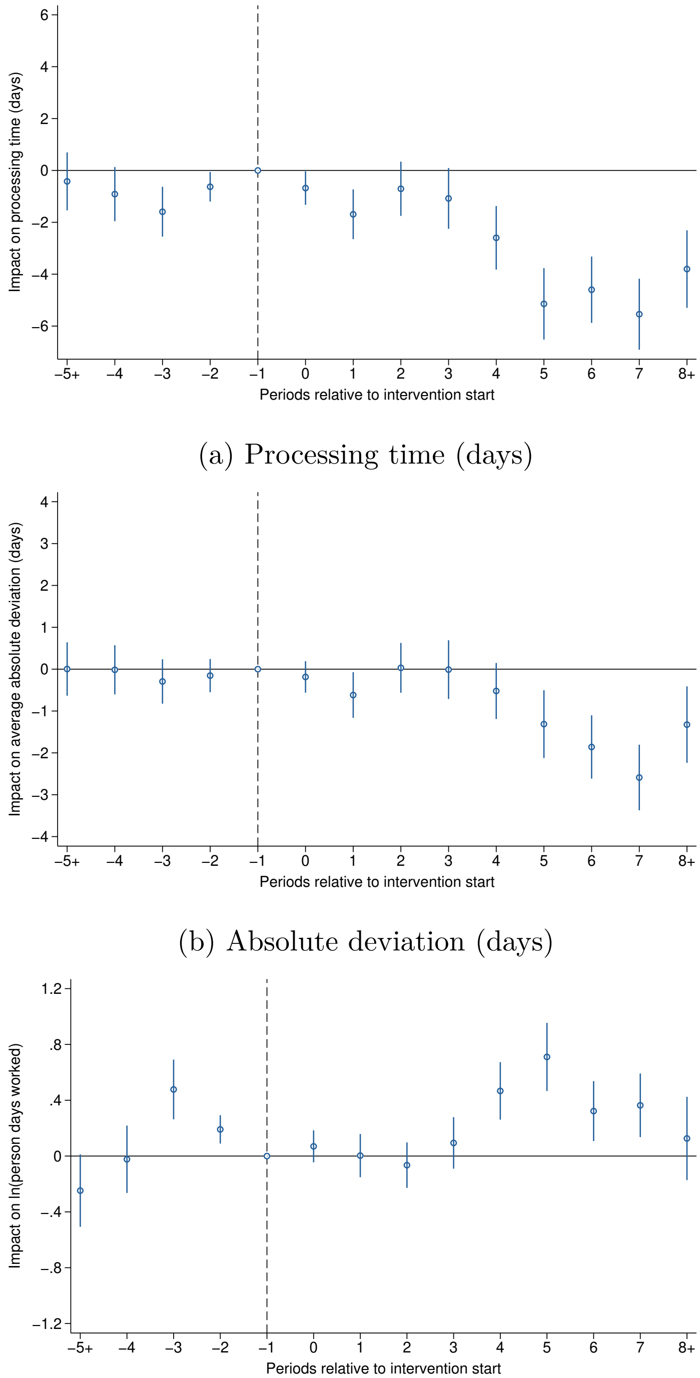


(a) Performance metrics - as reported by District POs



(b) Implementation challenges - self-reported

Figure 1: MGNREGS administrative environment for subdistrict officers



(a) Processing time (days)

(b) Absolute deviation (days)

(c) Log person-days worked

Figure 2: Dynamics of PayDash impacts

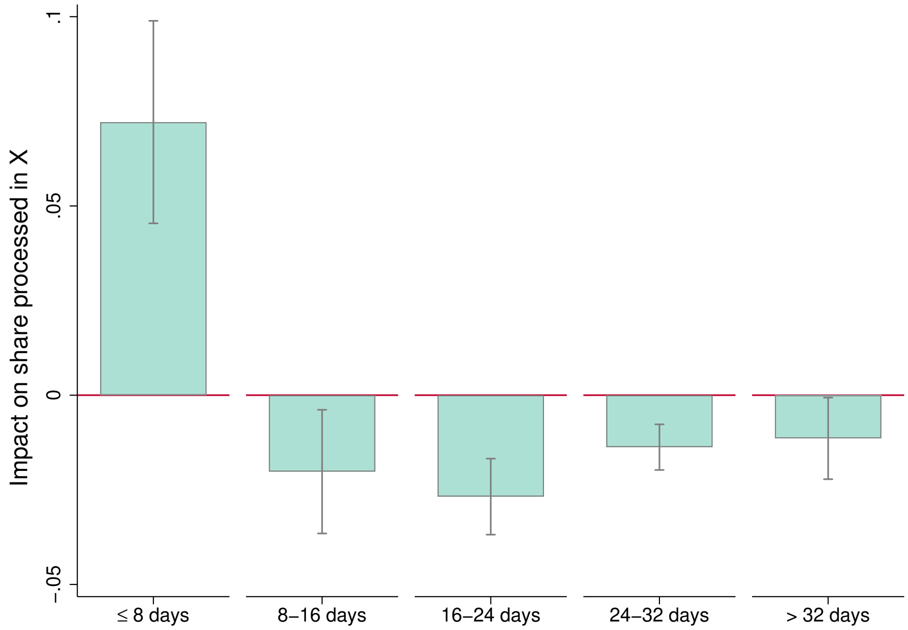
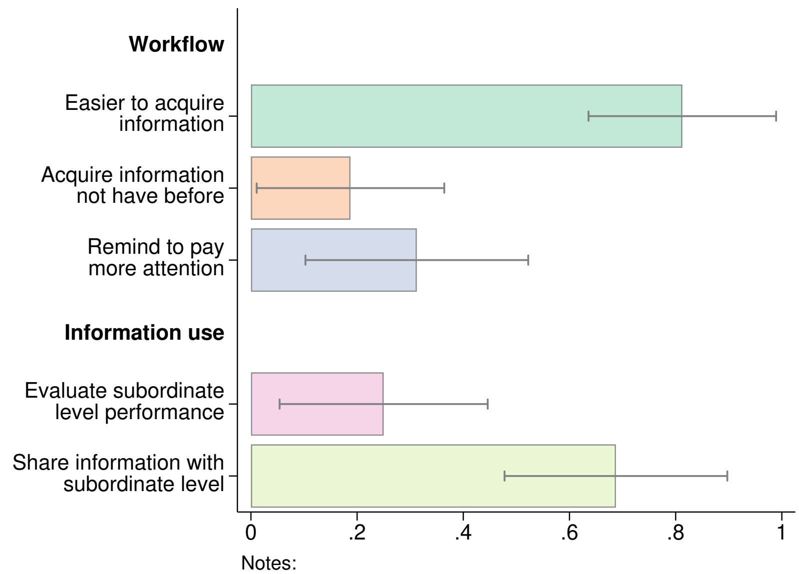
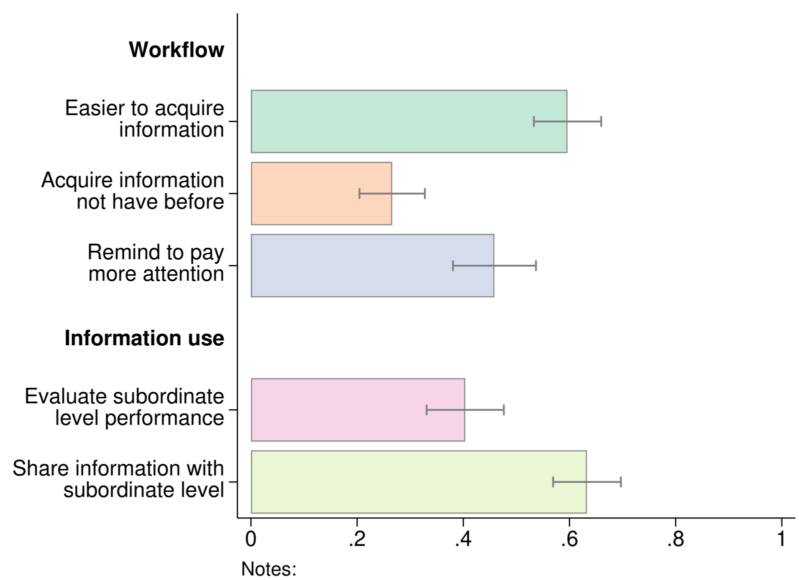


Figure 3: Impacts of PayDash on processing time distribution



(a) District POs



(b) Subdistrict POs

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

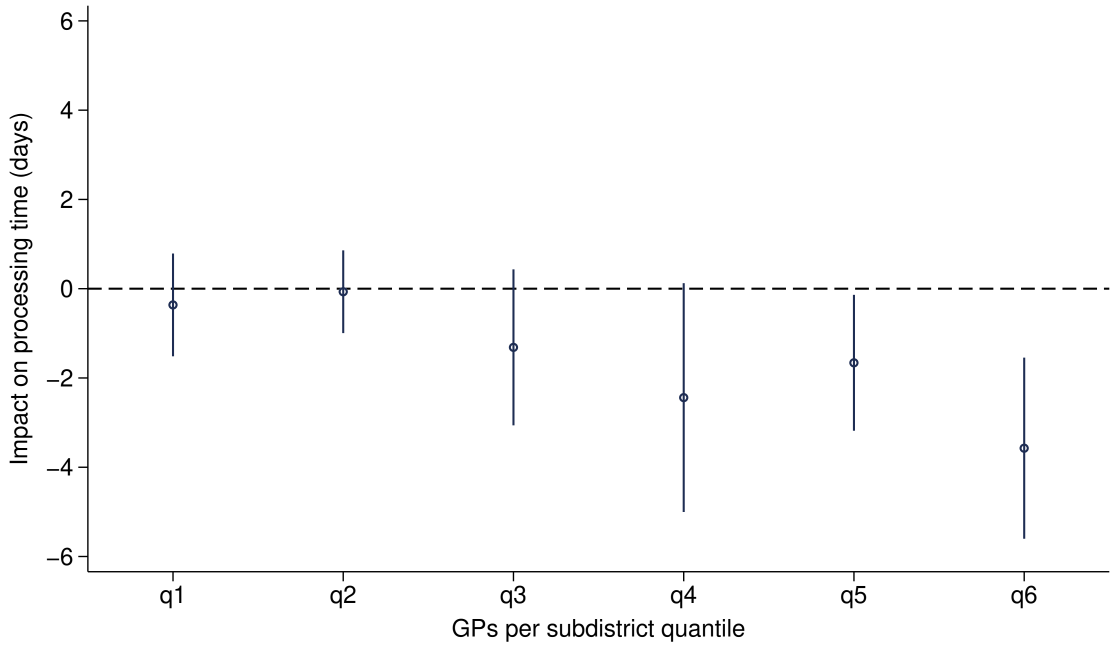


Figure 5: Heterogeneity in PayDash impact by administrative structure

Table 1: Officer monthly PayDash usage

	Subdistrict officers			District officers		
	Sessions	Duration (min)	Calls and messages	Sessions	Duration (min)	Calls and messages
	(1)	(2)	(3)	(4)	(5)	(6)
Single-level PayDash	4.72	27.62	0.69	4.80	27.96	20.39
	[9.17]	[84.64]	[8.16]	[9.04]	[69.45]	[75.63]
Both levels impact	0.74	0.44	0.18	-0.99	-14.14	-21.71
	(0.81)	(6.21)	(0.60)	(2.05)	(15.83)	(17.51)
Observations	3,251	3,251	3,251	411	411	411

Notes: Columns report means and standard deviations of the listed officer PayDash usage variable, calculated as the sum of CEO and PO usage within a given subdistrict-month (columns 1 through 3) or district-month (columns 4 through 6) and restricted to treatment months in localities receiving PayDash only at the listed administrative level. 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: PayDash impacts on worker payment processing

	Processing time (days)		Above mandate length		Absolute deviation (days)		Log total attendance registers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any PayDash (β)	-1.417***		-0.071**		-0.517**		0.186**	
	(0.382)		(0.034)		(0.226)		(0.079)	
District Only PayDash (β_1)		-1.518**		-0.073		-0.632*		0.234*
		(0.745)		(0.050)		(0.376)		(0.119)
Subdistrict Only PayDash (β_2)		-1.673***		-0.045		-0.498		0.141
		(0.568)		(0.032)		(0.300)		(0.099)
Combination (β_3)		-1.160**		-0.086		-0.437		0.178
		(0.500)		(0.052)		(0.326)		(0.113)
Observations	14,553	14,553	14,553	14,553	14,553	14,553	14,553	14,553
$\beta_1 = \beta_2 = \beta_3$, p-value		0.742		0.667		0.911		0.814
Control outcome mean	13.25	13.25	0.72	0.72	6.50	6.50	5.76	5.76

Notes: Columns report estimates following Equation (1). Control means calculated over pre-intervention period. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 3: Effects of PayDash on household work volume

	Log total person-days worked		Log person-days per working household		Log total working households	
	(1)	(2)	(3)	(4)	(5)	(6)
Any PayDash (β)	0.172**		0.086***		0.086	
	(0.069)		(0.019)		(0.070)	
District Only PayDash (β_1)		0.287***		0.130***		0.157*
		(0.101)		(0.022)		(0.091)
Subdistrict Only PayDash (β_2)		0.169**		0.116***		0.053
		(0.082)		(0.027)		(0.073)
Combination (β_3)		0.082		0.030		0.052
		(0.099)		(0.029)		(0.104)
Observations	14,554	14,554	14,554	14,554	14,554	14,554
$\beta_1 = \beta_2 = \beta_3$, p-value		0.230		0.014		0.553
Control outcome mean	9.31	9.31	2.28	2.28	7.03	7.03

Notes: Columns report estimates following Equation (1). Control means calculated over pre-intervention period. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table 4: PayDash impacts on bureaucrat work quality and posting transfers

	Share of payment requests rejected		Audit irregularity index		Subdistrict posting transfer	
	(1)	(2)	(3)	(4)	(5)	(6)
Any PayDash (β)	-0.007		-0.029		-0.057	
	(0.005)		(0.056)		(0.044)	
District Only PayDash (β_1)		-0.006		0.004		-0.106**
		(0.007)		(0.070)		(0.051)
Subdistrict Only PayDash (β_2)		0.003		-0.030		0.029
		(0.008)		(0.056)		(0.055)
Combination (β_3)		-0.015**		-0.063		-0.073
		(0.006)		(0.056)		(0.051)
Observations	14,266	14,266	20,621	20,621	1,122	1,122
$\beta_1 = \beta_2 = \beta_3$, p-value		0.188		0.289		0.036
Control outcome mean	0.052	0.052	0.000	0.000	0.447	0.447

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

Table 5: PayDash effects on program demand, worksites, and officer knowledge

	Community work demand		Log total active worksites		Subdistrict officer knowledge gap	
	(1)	(2)	(3)	(4)	(5)	(6)
Any PayDash (β)	0.124**		0.242***		-0.078*	
	(0.061)		(0.066)		(0.042)	
District Only PayDash (β_1)		0.088		0.294**		-0.067
		(0.076)		(0.118)		(0.056)
Subdistrict Only PayDash (β_2)		0.102		0.256**		-0.100**
		(0.076)		(0.111)		(0.048)
Combination (β_3)		0.183**		0.195**		-0.072
		(0.074)		(0.075)		(0.048)
Observations	20,621	20,621	12,308	12,308	176	176
$\beta_1 = \beta_2 = \beta_3$, p-value		0.435		0.703		0.780
Control outcome mean	0.297	0.297	5.314	5.314	0.418	0.418

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

Table 6: PayDash usage impacts of exogenous shock to data availability

	Subdistrict officers		District officers	
	Sessions	Duration (min)	Sessions	Duration (min)
	(1)	(2)	(3)	(4)
Outage month	-2.86***	-17.71***	-2.31**	-8.06*
	(0.62)	(3.92)	(0.90)	(4.09)
Observations	1,016	1,016	160	160
Non-outage month mean	5.03	24.51	4.58	15.13

Notes: Columns report estimates from regressions at the locality-month level of the listed variable on an indicator taking value one in the outage month (July 2017) and strata 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 7: Heterogeneity by administrative structure and workload

	Processing time (days)					
	(1)	(2)	(3)	(4)	(5)	(6)
Any PayDash						
* High GPs per subdistrict	-1.882**	-2.165**	-2.940***		-0.709	-0.550
	(0.834)	(0.073)	(1.089)		(0.804)	(1.016)
* High subdistricts per district		-0.729	-0.431			0.156
		(0.923)	(1.126)			(0.976)
* High subdistrict PO workload				-2.787***	-2.440***	-3.758***
				(0.773)	(0.798)	(0.711)
* High district PO workload						0.095
						(0.639)
Any PayDash	-0.677*	-0.010	-6.666	-0.267	-0.131	-0.386
	(0.399)	(0.929)	(11.458)	(0.396)	(0.442)	(9.068)
Observations	14,553	14,553	13,487	14,553	14,553	13,487
Interacted additional controls			X			X
Control outcome mean (high)	16.79	16.79	16.79	16.13	16.13	16.13
Control outcome mean (low)	12.22	12.22	12.22	12.41	12.41	12.41

Notes: All columns report estimates following Equation (1) with additional terms included as described subsequently. Columns (1) through (3), (5), and (6) also 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 (2), (3), and (6) additionally include an interaction of the treatment indicator with an indicator for being an above-median district in terms of number of subdistricts. Columns (4) through (6) also 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. Column (6) further includes an interaction of the treatment indicator with an indicator for being an above-median district in terms of baseline district PO workload index. Columns (3) and (6) additionally include interactions (not shown) of the treatment indicator with district-level measures of rural population share and log population, the baseline district PO age, gender, and post-graduate education completion, and the district-level baseline averages of age, gender, and post-graduate education completion 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) through (3) and in terms of average baseline subdistrict PO workload index in columns (4) through (6). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Appendix A: Figures and Tables

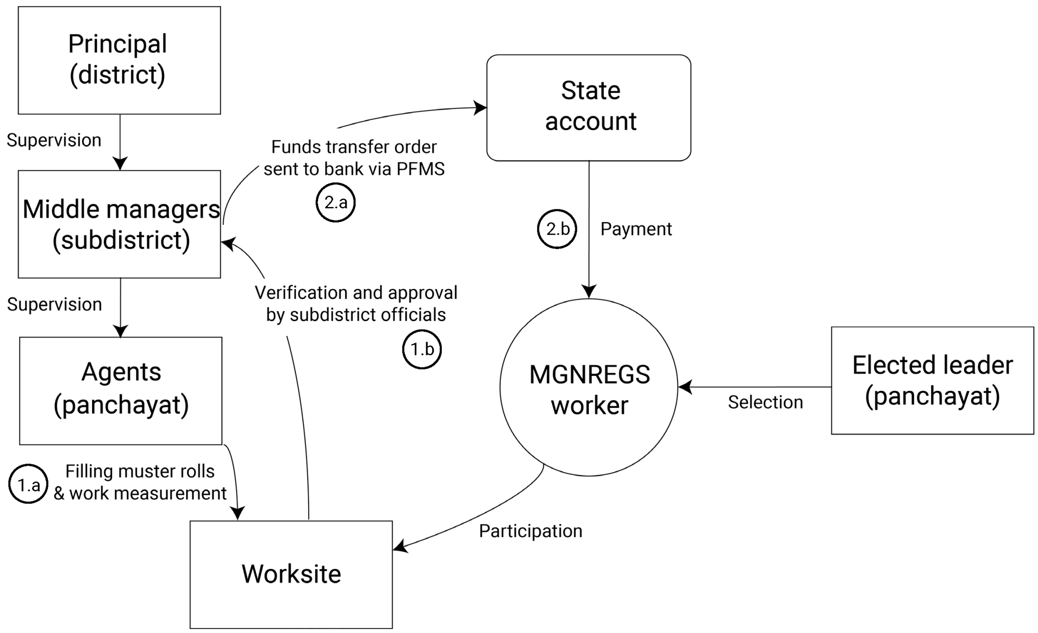


Figure A1: MGNREGS work, verification, and payment process

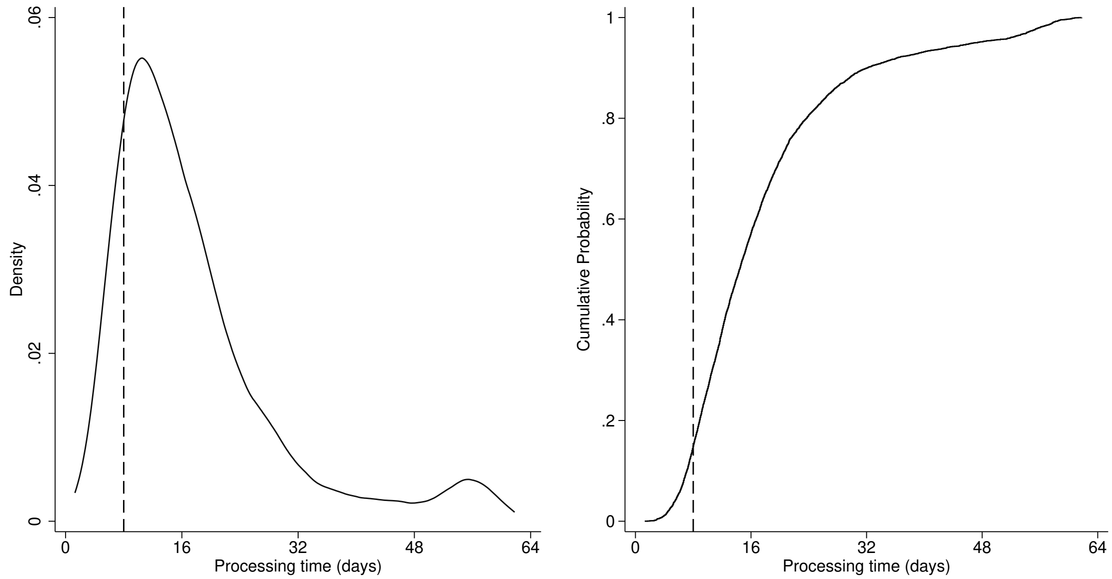
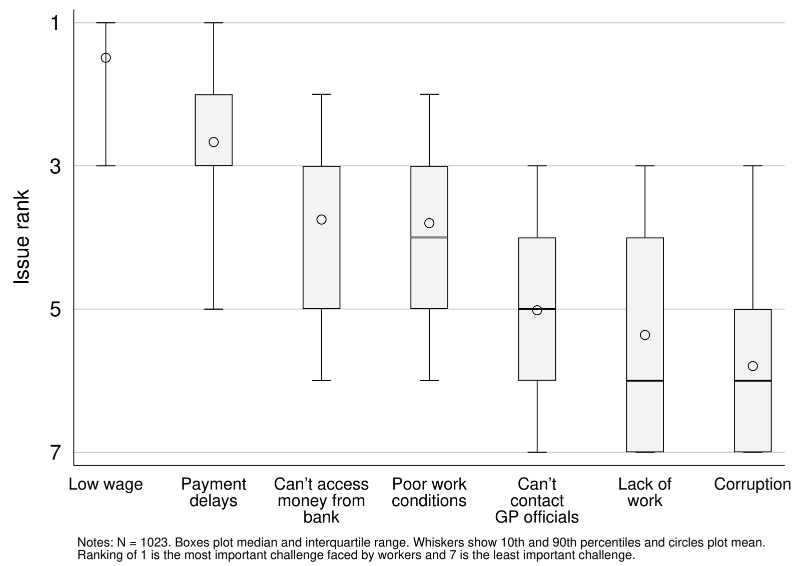
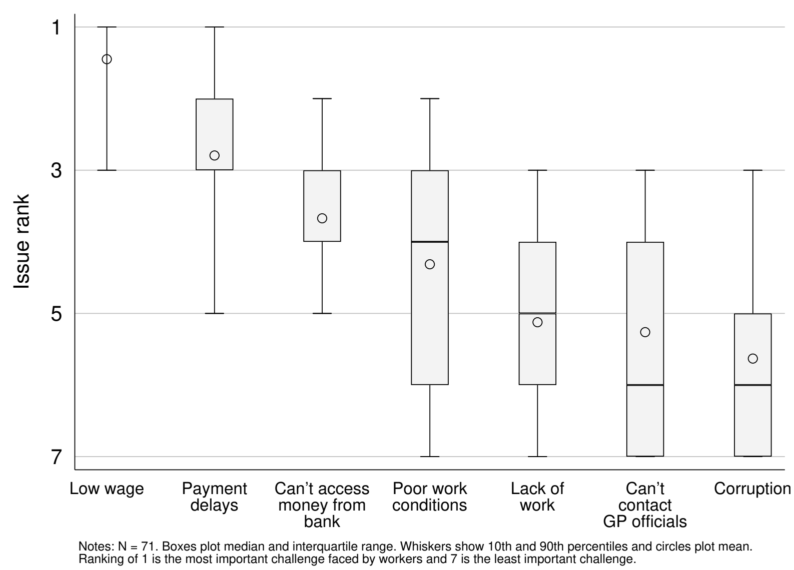


Figure A2: Payroll processing times prior to intervention



(a) As reported by subdistrict officers



(b) As reported by district POs

Figure A3: Challenges faced by MGNREGS workers

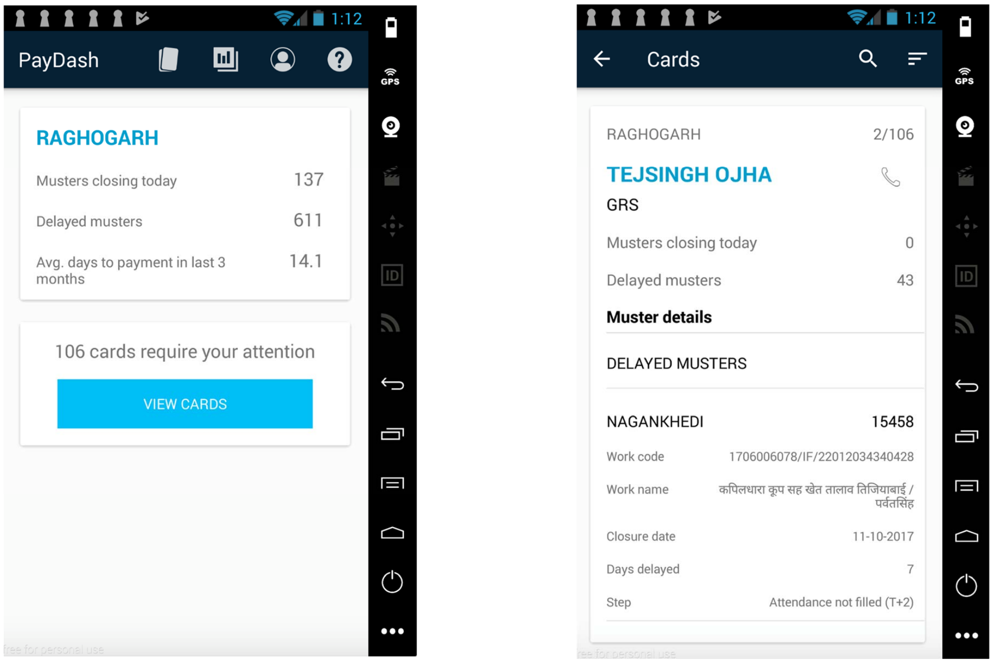


Figure A4: PayDash app home screen providing a daily-updated overview of payment processing status within an officer's jurisdiction (L). App screen with information about a local official. The app shows payment documents pending and allows officers to directly contact the individual responsible for processing the document. (R)

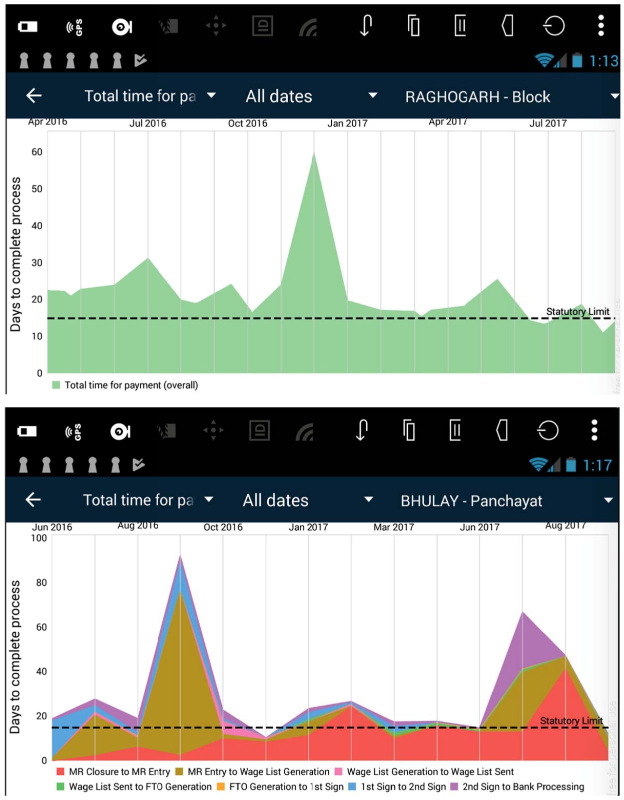


Figure A5: The performance dashboard of the Block PayDash app provides a historical overview of subdistrict and village-level performance.

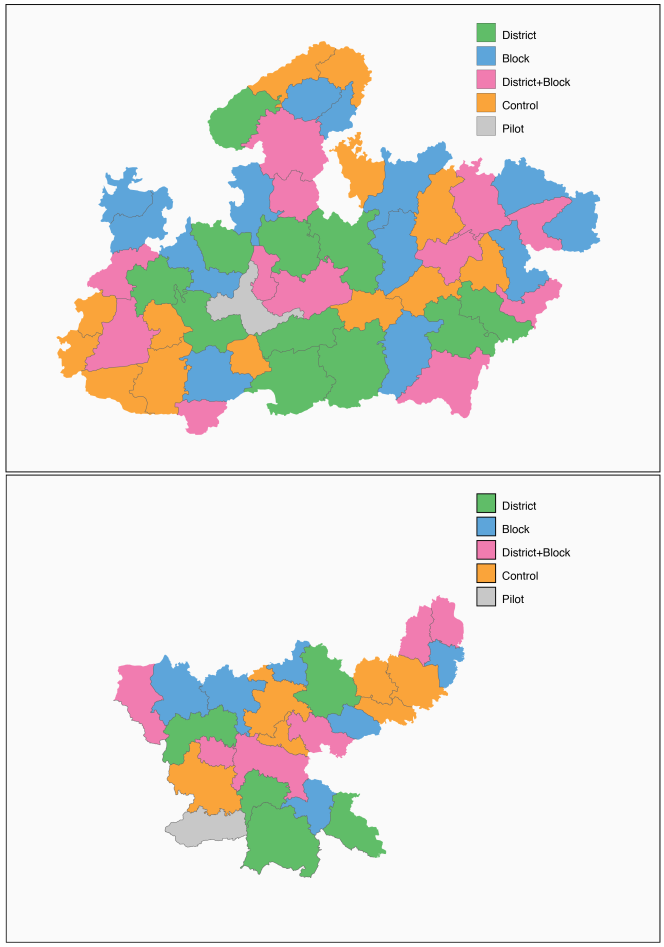


Figure A6: District randomized treatment assignments - Madhya Pradesh (top) and Jharkhand (bottom)

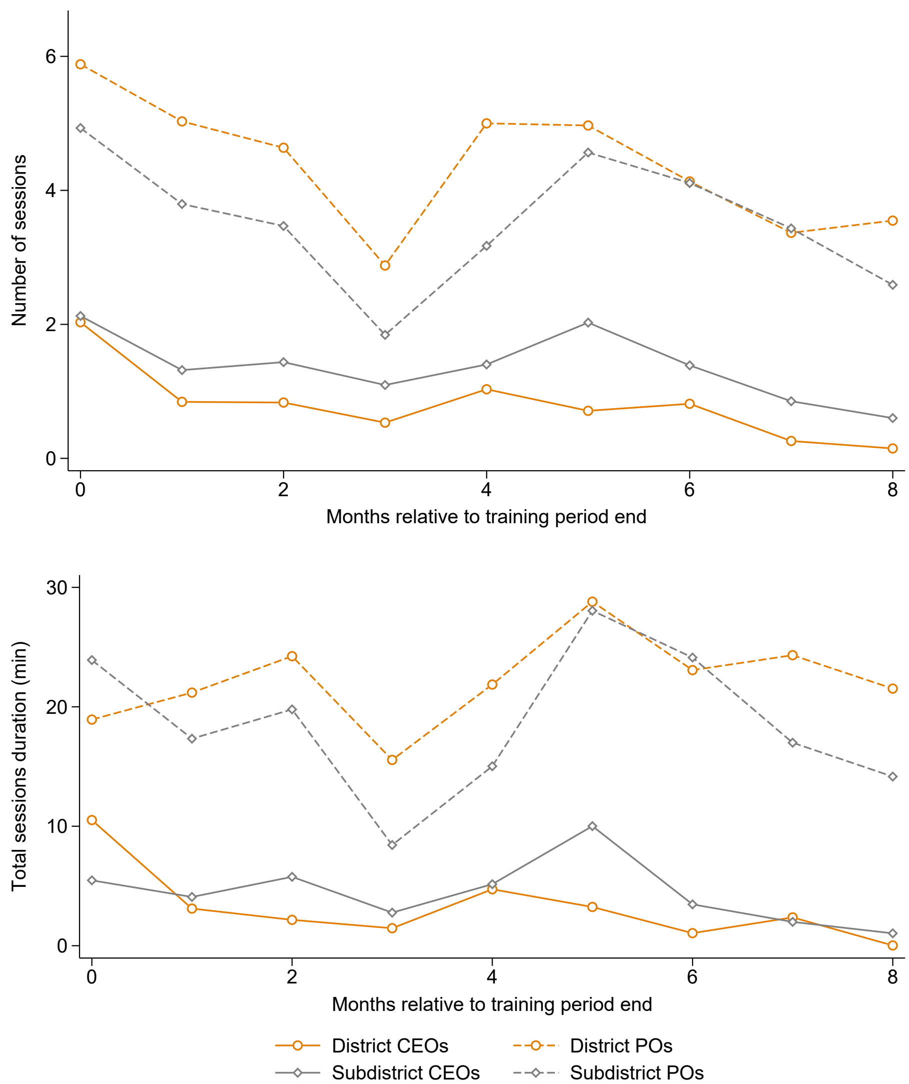
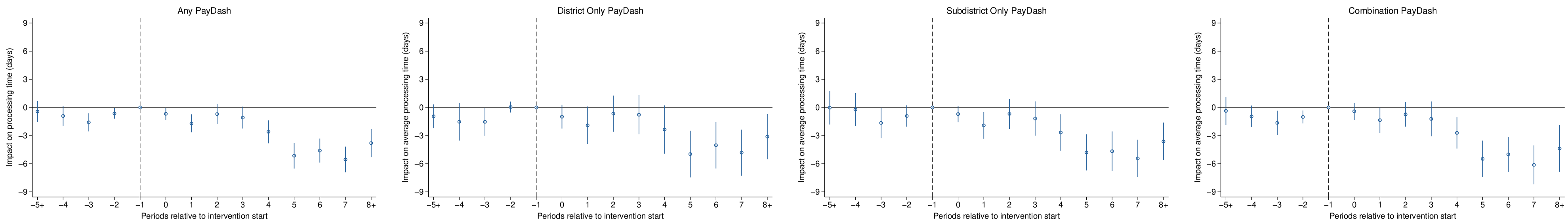
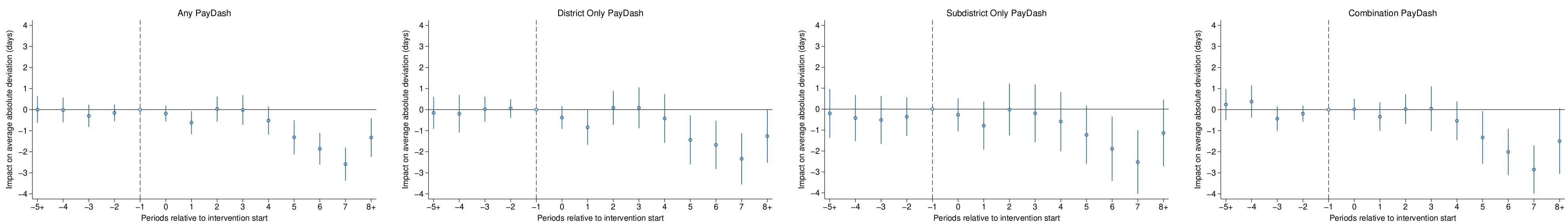


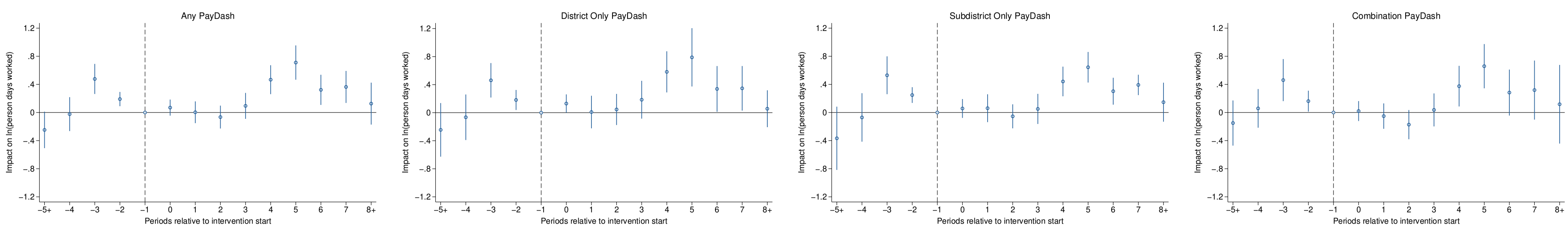
Figure A7: PayDash usage over time



(a) Processing time (days)



(b) Absolute deviation (days)



(c) Log person-days worked

Figure A8: PayDash impacts - by treatment arm

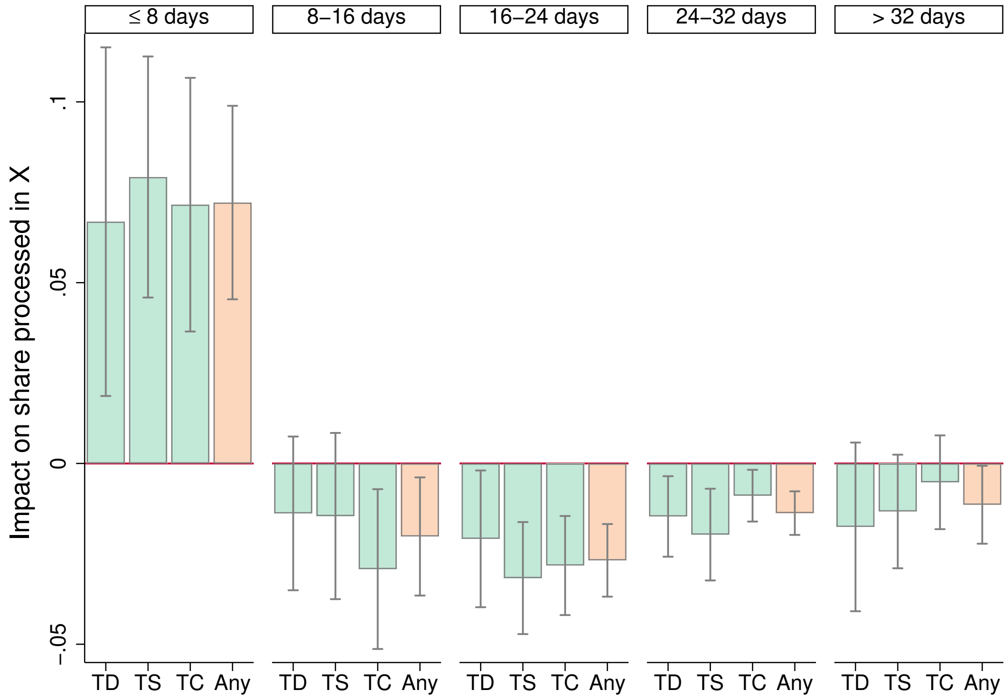
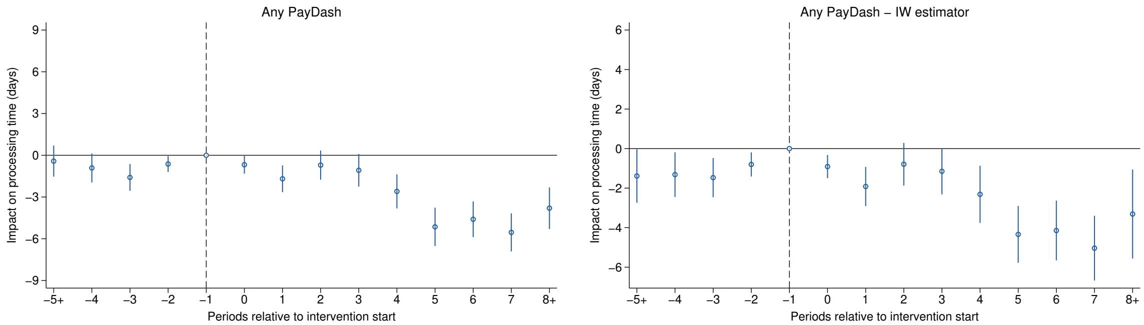
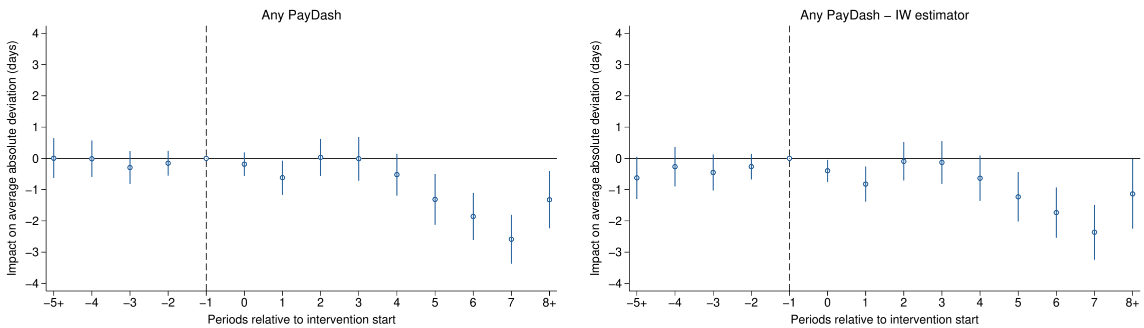


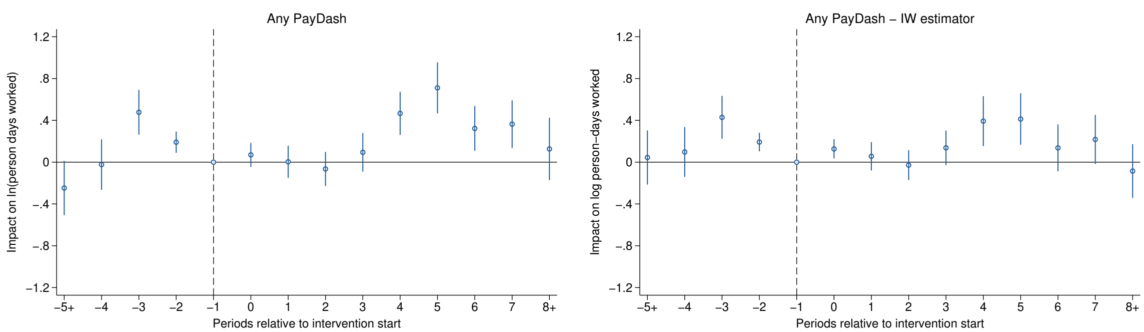
Figure A9: Impacts of PayDash on processing time distribution - by treatment arm



(a) Processing time (days)



(b) Absolute deviation (days)



(c) Log person-days worked

Figure A10: IW estimator comparison

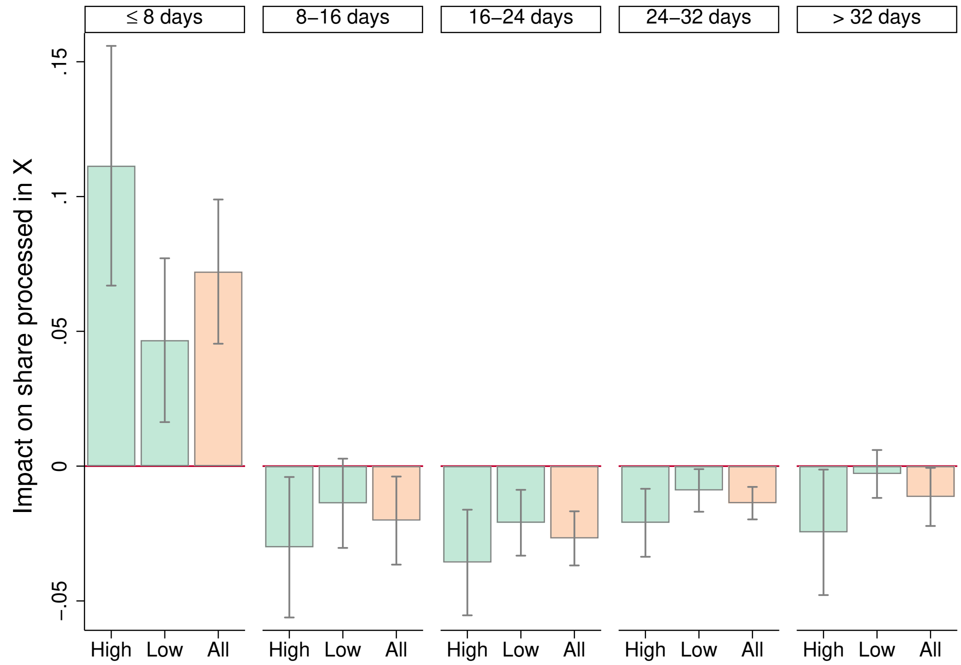


Figure A11: PayDash impacts on processing time distribution - by GPs per subdistrict

Table A1: Baseline characteristics

	Overall Mean (1)	District Only (2)	Subdistrict Only (3)	Combination (4)	Joint p-value (5)	Obs (6)
Panel A: District and program characteristics						
Subdistricts	7.70	1.20	-0.41	0.44	0.455	73
	[3.99]	(1.14)	(0.79)	(1.11)		
Average GPs per subdistrict	56.69	-0.84	7.09*	3.24	0.288	73
	[28.82]	(4.60)	(3.92)	(3.06)		
Total population (x1,000)	1420.60	-197.68	-138.28	-22.35	0.815	73
	[621.90]	(259.67)	(214.67)	(222.19)		
Rural population share	77.26	2.82	0.11	-3.56	0.592	73
	[15.88]	(4.89)	(5.56)	(5.29)		
Processing time (days)	18.86	-1.58	0.22	-0.76	0.613	73
	[6.30]	(1.61)	(1.46)	(1.43)		
Absolute deviation (days)	10.41	-0.65	0.31	-0.11	0.681	73
	[3.15]	(0.78)	(0.78)	(0.72)		
Person-days worked (x1,000)	2355.39	784.01*	-70.32	308.79	0.182	73
	[1281.83]	(449.14)	(287.24)	(378.68)		
Attendance registers (x1,000)	42.43	12.67	-2.17	-0.14	0.595	73
	[31.42]	(11.74)	(6.55)	(7.68)		
Share of payment requests rejected	0.09	-0.00	0.01	0.02*	0.272	73
	[0.04]	(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)		
Online data access daily	0.96	0.11	0.11	0.06	0.398	68
	[0.21]	(0.07)	(0.07)	(0.09)		
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)		
Online data access daily	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: In each row, Column (1) presents the overall mean and standard deviation for the listed variable. Columns (2) through (4) present regression coefficients and standard errors from a regression of the listed variable on treatment arm indicators, with control as the omitted group. Additionally included in each regression are randomization strata fixed effects, as well as an indicator for being a program officer in Panels B and C. Column (5) presents the p-value from an F-test of the joint hypothesis of zero-valued coefficients on the treatment arm indicators. Column (6) gives the number of observations. Standard errors are heteroskedasticity robust and, in Panels B and C, clustered by district. Variables in Panel A are at the district level and generated from MGNREGS administrative data for the year prior to intervention start (February 2016-January 2017) and 2011 census data. Variables in Panels B and C are at the district and subdistrict officer level, repsectively, and generated from the baseline officer surveys.

Table A2: Additional baseline characteristics

	Overall Mean	District Only	Subdistrict Only	Combination	Joint p-value	Obs
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: District and program characteristics						
Person-days per working household	13.62	0.83	-0.96	-0.00	0.670	73
	[4.03]	(1.37)	(1.08)	(1.09)		
Working households (x1,000)	12.25	3.55	0.31	2.32	0.377	73
	[7.65]	(2.44)	(1.63)	(2.41)		
Standard deviation (days)	16.66	-0.84	1.32	0.31	0.453	73
	[4.13]	(1.21)	(1.56)	(1.21)		
Worker wage expenditure (x1,000,000 Rs.)	376.43	111.76	-12.48	55.12	0.244	73
	[205.22]	(71.99)	(48.06)	(61.76)		
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 prior to intervention start (February 2016-January 2017), generated from MGNREGS administrative data. For additional details on table construction, see the Table 1 notes.

Table A3: Officer monthly PayDash usage - position-wise

	Sessions		Duration (min)		Calls and messages	
	POs	CEOs	POs	CEOs	POs	CEOs
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. District officers						
District Only PayDash	4.39	0.43	26.61	1.48	17.17	0.12
	[9.42]	[1.98]	[71.38]	[8.46]	[68.76]	[1.30]
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
Panel B. Subdistrict officers						
Subdistrict Only PayDash	3.08	1.29	19.99	5.06	0.52	0.08
	[7.45]	[4.48]	[74.53]	[25.82]	[7.41]	[1.17]
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

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. 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 A4: MGNREGS worker composition

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

Notes: Columns report estimates following Equation (1). Control means calculated over pre-intervention period. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A5: Longer term impacts on officer transfers - Madhya Pradesh

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

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

Table A6: Audit index - components

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

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

Table A7: Heterogeneity in PayDash impacts by administrative structure - treatment arms

	Processing time (days)			
	(1)	(2)	(3)	(4)
District Only PayDash				
* High GPs per subdistrict	-2.849*	-2.939		-1.404
	(1.613)	(2.018)		(1.310)
* High subdistricts per district		-0.344		
		(2.289)		
* High subdistrict PO workload			-3.707***	-2.999**
			(1.304)	(1.258)
District Only PayDash	-0.482	-0.158	-0.057	0.173
	(0.584)	(2.272)	(0.613)	(0.695)
Subdistrict Only PayDash				
* High GPs per subdistrict	-1.443	-2.283*		-0.228
	(1.297)	(1.282)		(1.743)
* High subdistricts per district		-2.367**		
		(1.059)		
* High subdistrict PO workload			-2.536**	-2.484
			(1.100)	(1.700)
Subdistrict Only PayDash	-0.945	1.192	-0.284	-0.205
	(0.853)	(1.139)	(0.594)	(0.605)
Combination PayDash				
* High GPs per subdistrict	-1.257	-0.951		-0.493
	(1.039)	(0.919)		(1.120)
* High subdistricts per district		0.552		
		(1.140)		
* High subdistrict PO workload			-2.120**	-1.913*
			(1.015)	(1.128)
Combination PayDash	-0.713	-1.229	-0.421	-0.318
	(0.518)	(1.129)	(0.562)	(0.613)
Observations	14,553	14,553	14,553	14,553
D + S = C, p-value (high)	0.052		0.013	
D + S = C, p-value (low)	0.505		0.934	
D = S = C, p-value (high)	0.724		0.649	
D = S = C, p-value (low)	0.895		0.893	
Control outcome mean (high)	16.79	16.79	16.13	16.13
Control outcome mean (low)	12.22	12.22	12.41	12.41

Notes: All columns report estimates following Equation (1) with additional terms included as described subsequently. Columns (1), (2), and (4) also include 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) additionally includes an interaction of the treatment arm indicators with an indicator for being an above-median district in terms of number of subdistricts. Columns (3) and (4) also include 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 hgh 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 (3). 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) and (4). Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A8: Association of administrative structure and workload

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

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

Table A9: Workload index - components

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

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

Table A10: Heterogeneity in PayDash impacts by administrative structure - continuous

	Processing time (days)					
	(1)	(2)	(3)	(4)	(5)	(6)
Any PayDash						
* GPs per subdistrict	-0.041***	-0.044**	-0.040*		-0.494	-0.025
	(0.015)	(0.018)	(0.022)		(0.918)	(0.023)
* Subdistricts per district		-0.036	0.272*			0.220
		(0.092)	(0.157)			(0.166)
* Subdistrict PO workload				-4.326***	-3.281*	-2.712*
				(1.385)	(1.728)	(1.628)
* District PO workload						-0.243
						(0.876)
Any PayDash	0.549	1.077	3.746	-1.380***	-0.494	2.911
	(0.671)	(1.426)	(12.183)	(0.377)	(0.918)	(11.333)
Observations	14,553	14,553	13,487	14,553	14,553	13,487
Interacted additional controls			X			X

Notes: All columns report estimates following Equation (1) with additional terms included as described subsequently. Columns (1) through (3), (5), and (6) also include an interaction of the treatment indicator with the district-level average number of panchayats per subdistrict. Columns (2), (3), and (6) additionally include an interaction of the treatment indicator with number of subdistricts. Columns (4) through (6) also include an interaction of the treatment indicator with the average value of the baseline subdistrict PO workload index. Column (6) further includes an interaction of the treatment arm indicator with the baseline district PO workload index. Columns (3) and (6) additionally include interactions (not shown) of the treatment indicator with district-level measures of rural population share and log population, the baseline district PO age, gender, and post-graduate education completion, and the district-level baseline averages of age, gender, and post-graduate education completion for subdistrict POs. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A11: Heterogeneity in PayDash impacts by administrative structure - additional outcomes

	Above mandate length	Absolute deviation (days)	Log total attendance registers	Log total person-days worked	Log person-days per working household	Log total working households
	(1)	(2)	(3)	(4)	(5)	(6)
Any PayDash						
* High subdistrict PO workload	-0.145**	-1.642***	0.070	0.055	0.079*	-0.023
	(0.062)	(0.370)	(0.131)	(0.106)	(0.042)	(0.102)
* High GPs per subdistrict	-0.131*	-0.497	0.266	0.009	-0.019	0.028
	(0.074)	(0.573)	(0.177)	(0.150)	(0.054)	(0.128)
Any PayDash	-0.476	0.829	6.465***	5.098***	0.782	4.316***
	(0.733)	(5.330)	(2.065)	(1.730)	(0.499)	(1.489)
Observations	13,487	13,487	13,487	13,488	13,488	13,488
Interacted additional controls	X	X	X	X	X	X
Control outcome mean (high)	0.909	6.712	5.606	9.307	2.548	6.759
Control outcome mean (low)	0.662	6.396	5.813	9.305	2.202	7.102

Notes: All columns report estimates following Equation (1) with additional terms included as described subsequently. Additionally included are interactions of the treatment indicator with indicators for being an above-median district in terms of the average value of the baseline subdistrict PO workload index and average number of panchayats per subdistrict. Also included (not shown) are interactions of the treatment indicator with: indicators for being an above-median district in terms of number of subdistricts and baseline district PO workload index; district-level measures of rural population share and log population; baseline district PO age, gender, and post-graduate education completion; and the district-level averages of baseline age, gender, and post-graduate education completion 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 baseline subdistrict PO workload index. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Table A12: PayDash usage heterogeneity

	Subdistrict officers		District officers	
	Sessions	Duration (min)	Sessions	Duration (min)
	(1)	(2)	(3)	(4)
High subdistrict PO workload	1.56*	16.51***	-0.74	-0.53
	(0.90)	(6.10)	(1.85)	(8.38)
High GPs per subdistrict	-1.27	-9.67	3.09*	14.84
	(0.99)	(7.89)	(1.82)	(11.30)
High district PO workload	0.87	2.82	-0.42	-5.33
	(0.68)	(4.43)	(1.64)	(10.39)
High subdistricts per district	-0.75	-2.96	-2.97	-11.61
	(1.66)	(11.33)	(1.89)	(11.89)
Both levels PayDash	0.80	3.14	-3.43*	-26.20
	(0.73)	(5.69)	(2.00)	(17.16)
Observations	3,716	3,716	487	487
Outcome mean	3.68	21.58	3.82	19.57

Notes: Columns report estimates from regressions at the district- or subdistrict-month level of the listed program officer PayDash usage variable on 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, baseline district PO workload index, and number of districts. Also included are month and strata fixed effects, and an indicator for PayDash provision at both officer levels. The sample is restricted to treatment months in localities receiving PayDash at the corresponding officer level. Standard errors clustered at the district level in parentheses. Significant at *10 percent, **5 percent,***1 percent.

Appendix B

B.1 PayDash training

To introduce officers to PayDash, we invited the relevant government officials in the trainging session cachement area - district and subdistrict CEOs and POs - to a half-day session.

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

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

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

B.2 Randomization strata

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

B.3 Social audits

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

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

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

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

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