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Biometric Smartcards and payment disbursement

A replication study of a state capacity-building experiment in India

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Biometric Smartcards and payment disbursement: a replication study of a state capacity-building experiment in India

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Summary

Most low- and middle-income countries lack the infrastructure to efficiently process and deliver payments to beneficiaries of welfare programs. As a result, many poor people are financially excluded or receive only a portion of the funds intended for them. There are few empirical studies for policy reference to identify and justify potential returns of public investment in building technology-based infrastructure. This study replicates a recent experimental study that fills this empirical gap by examining the effect of biometrically authenticated payments, “Smartcards,” on India’s two largest welfare programs (a work-for-payment scheme and a national pension program). We evaluate the original study’s findings and obtain comparable outcomes – that Smartcards decrease the time lag for recipients to receive funds, reduce leakages of benefits and increase enrollment rates in the two programs. We also examine the robustness of the original study to outliers, alternative model specifications, changes in estimation methods and treatment effects heterogeneity bias.

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Abbreviations and acronyms

BL	Base line
FE	Fixed effect
GLMM	Generalized linear mixed model
GP	Gram panchayat
ITT	Intent to treat
LNG	Liquefied Natural Gas
MEA	Measurement and estimation analysis
NREGS	National Rural Employment Guarantee Scheme
OLS FE	Ordinary least square fixed effect
PC	Principal component
RE	Random effect
SSP	Social security pensions
TOT	Treatment on the treated

1. Introduction

Lack of efficient and adequate technology-enabled infrastructure, high poverty rates and corruption constitute a few of the major economic problems hindering inclusive growth (de Mello and Dutz 2012), optimal delivery of public services and distribution of public transfers in low- and middle-income countries. India, the world's second most populated nation, has achieved significant success in improving welfare in most cities where there is technological advancement, but more effort is required in rural areas to reduce poverty, provide access to efficient payment infrastructure and facilitate the disbursement of funds to the poorest of the poor without leakages. Estimates from the World Bank (2016) reveal that more than half of the population in India is living on less than US$3.90 (Rs 206.3)[1] a day and only 32.6 percent of rural residents can withdraw or receive remittances through formal financial institutions. The Internet and Mobile Association of India (Pandey 2018) has reported that only 16 percent of the rural dwellers use the Internet to verify and process remittances from government or family and friends, compared to 44 percent in the urban areas. The lack of adequate and widespread technology-based infrastructure and formalized institutions are hindering government efforts to successfully deliver public services, target the poor and disburse payments effectively to achieve better welfare outcomes.

These problems are not prevalent only in India; similar issues confront other low- and middle-income countries, in varying degrees. One pathway to ameliorate such welfare issues is to invest and develop appropriate (and empirically verified) modern technological infrastructure for disbursing money to targeted beneficiaries and improving public service delivery. The technology must align with the needs of the poor, serve as an audit tool for reducing corruption (leakages) and facilitate state capacity development. As Afridi and Iversen (2014) note, audit tools can improve government service delivery through employment generation and reduction in leakages if efficiently implemented in a country such as India, where officials are constantly looking for rent-seeking loopholes.

The highlighted welfare issues and associated public service delivery inefficiencies with a lack of technology-enabled infrastructure motivates us to validate the evidence-based policy options reported in Muralidharan and colleagues (2016) for addressing those issues. We validate by replicating their study, *Building State Capacity: Evidence from Biometric Smartcards in India.* The goal of validating the study is to provide more credibility in support of public investments in technology-based infrastructure to enhance the efficiency of public service delivery and reduce corruption. Muralidharan and colleagues investigate the impact of biometrically authenticated payment infrastructure (Smartcards) on beneficiaries of the two largest employment programs in the Indian state of Andhra Pradesh – the National Rural Employment Guarantee Scheme (NREGS) and Social Security Pension (SSP).

[1] The exchange rate used in this paper is US$1 to 66.5580 rupees (Rs). This is the prevailing rate as at 17 October 2016, sourced from https://www.oanda.com/currency/converter/.

The aim of introducing fingerprint scanning[2] as an authentication process (i.e. verification and audit system) for payments in the two largest welfare programs (NREGS and SSP) in India is to specifically target those in need of welfare packages and promote effective public disbursement of payments to the poor in the selected districts of Andhra Pradesh. The Smartcard project is a key part of India's digital reforms, which have registered more than 1.1 billion people through the biometric authentication scheme (Gelb et al. 2018). The Andhra Pradesh biometric authentication technology has enabled the establishment and operation of several employment, consumption and income programs to target poor people. Similarly, it facilitates unrestricted access to an anti-poverty program that enhances government technical capacity to enable prompt payment transfers (Pritchett 2009), guard against corruption, which often leads to the leakage – i.e. theft of money meant for the poor by government officials (Niehaus and Sukhtankar 2013; Muralidharan et al. 2014), improve public social service delivery (Afridi and Iversen 2014) and reform India's complex system of subsidies, benefits and transfers, which accounts for more than US$60 billion in annual spending (Gelb et al. 2017).

Muralidharan and colleagues' large-scale randomized experiment provides well-established and non-theoretical evidence on the benefits of investing in state capacity building (e.g. secure payment infrastructure) for improving development and social welfare. The original study contributes to the growing and conflicting literature on the effect of technology on corruption in low- and middle-income countries. The authors reveal that large-scale institutional supports for building capacity can increase the impact of technological solutions on household earnings, participation in employment programs (i.e. public service delivery), reduction of funds leakages and other forms of corruption.

The evidence of welfare improvement and reported gains from the use of Smartcards reported in the original paper can further contribute to the achievement of 9 of the 17 Sustainable Development Goals[3] set by the United Nations Development Programme, especially for low-income countries such as India. This constitutes another justification for this replication study to validate Muralidharan and colleagues' findings and provide additional evidence to support the use of Smartcards in other low- and middle-income countries. The outcomes of this replication will help those low- and middle-income countries determine how to use the evidence to effectively target the most vulnerable people in need of welfare packages and distribute payments and improve government service delivery.

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[2] As described in Muralidharan and colleagues (2016, p.2903), the Smartcard holds the beneficiary's biometric data (all 10 fingerprints), digital photograph and bank account details. The card is used as a form of identification through matching the scanned fingerprints at the point-of-service collection with a unique biometric record in the database. The matching process is random and can be unreliable in authenticating transactions for multiple reasons, including technical issues and nonmatching of fingerprints. Other associated and evolving issues are extensively discussed in Afridi and colleagues (2017) and Drèze and Khera (2018).

[3] The related goals to Muralidharan and colleagues' study are No Poverty (Goal 1), Zero Hunger (Goal 2); Good Health and Well-being (Goal 3); Gender Equality (Goal 5); Decent Work and Economic Growth (Goal 8); Reduced Inequalities (Goal 10); Responsible Consumption and Production (Goal 12); Strong Institutions (Goal 16); and Global Partnerships for the Goals (Goal 17). The full list of the Sustainable Development Goals is available at: https://www.undp.org/content/dam/undp/library/corporate/brochure/SDGs_Booklet_Web_En.pdf

Our replication study confirms Muralidharan and colleagues' findings, which provide evidence to justify the potential marginal benefits of public investment in building technology-based state capacity (e.g. a biometric payments system) to enhance public service delivery systems, improve access to transfer payments for the poor, alleviate poverty and reduce leakages (i.e. corruption). In the absence of such capacity, Olken (2006) describes that leakages of funds from their intended use due to corruption in the public system can create lack of incentives for policymakers to continue financing existing or future programs capable of improving the lives of the poor. Similarly, this replication study provides insights on additional benefits of biometric technology, such as efficiency (Gelb and Clark 2013), quality improvement, transparency and accountability (Lewis-Faupel et al. 2014) in the financing and allocation of money to participants enrolled in any welfare program.

Muralidharan and colleagues report that Smartcards in converted villages help participants earn more money, reduce leakages of funds, increase employment rates and facilitate prompt access to payment. These can complement government social and welfare efforts in India to achieve reductions in poverty, hunger and gender inequality, and improve good health and well-being, decent employment and productivity, income equality and domestic consumption. The Smartcards' ability to reduce corruption and improve transparency and accountability in the disbursement of money to the poor can also strengthen strong institutions and global partnership with international donors such as the Bill & Melinda Gates Foundation.

To verify and validate the welfare returns from investing in technology-based state infrastructure such as Smartcards, we extensively evaluate the original study. The remainder of this paper is divided in five sections. Section 2 is the push-button replication, in which we check whether the estimation codes can be executed "as is," without any modification. Section 3, the pure replication, confirms the consistency of the original results and checks whether the estimates from the replication exercise and the original study are the same. The robustness of the original results are examined in Section 4 under the measurement and estimation analysis (MEA). Section 5 is the theory of change analysis, in which new causal relationships are established. Section 6 concludes the replication study.

2. Push-button replication

We initially performed a push-button replication exercise, in which the original results are reproduced by running the codes "as is" without making any adjustments or reading through the estimation procedures and assumptions in the paper. The goal of the push-button replication as the first step is to assess the replicability of the original study without consulting the authors. The push-button replication exercise was successful, as we were able to reproduce the findings of Muralidharan and colleagues using the original data, methodology, code and statistical software without any modification.

3. Pure replication

The objective of a pure replication is to confirm the consistency of the original results. Instead of re-coding the entire findings using a different statistical application, such as R, we carefully audited the Stata do files, line by line, for data cleaning, transformation of variables and model estimations. During the code audit, we found that Muralidharan and colleagues had replaced missing values with zeros for some variables[4] in Section B of the NREGS and SPP survey data files. However, the changes do not influence the results. Also, while checking the number of observations in each surveyed district across different dimensions, we observed that there were some participants with Smartcards in the non-carded villages in the control group (Tables A8 and A9 in Appendix A). Instead of characterizing those cases as outliers, we realized that those recorded observations for the use of Smartcards in the non-carded villages were inevitable and could be regarded as a minor non-compliance issue with the randomization protocol.

3.1 Data

Muralidharan and colleagues have a publicly available replication folder on the *American Economic Review* website (Muralidharan et al. 2016), which we used for the pure replication. The folder contains other sub-folders, such as “analysis code,” “data” and “utilities.” The analysis code folder contains 35 Stata do files and 2 R program files. The data folder consists of 62 Stata data files for the baseline and endline surveys in 2010 and 2012. Some sections of the survey questionnaire are in separate data files. This includes household characteristics, census data, official records and leakage data. A comprehensive description of each of the data files is in a printable document file (ReadME.pdf) that comes with the replication folder. The utility directory contains Stata programs written by the original authors to automate part of the analyses and produce a better visualization. Replicating most of the reported findings requires combined use of different data files and some utility programs.

A master do file is used to connect all the folders, data and code files together to reproduce the original results, as presented in Section 3.3.

3.2 Brief description of the field experiment and method

Muralidharan and colleagues use a large-scale field experiment to randomize[5] the rollout of Smartcards, with the goal of identifying and understanding the gains from the use of biometric technology for authenticating beneficiaries’ identities before the disbursement of payments. As documented in the literature (Pritchett 2009 Niehaus and Sukhtankar 2013; Muralidharan et al. 2014; Banerjee et al. 2016; Gelb et al. 2018), such technology helps government deliver more efficient services and reduces the complexities associated with subsidies, transfers and benefits systems. The biometric authentication technology also has a spillover effect of reducing leakages of funds resulting from over-reporting the amount of work done or creating “ghost” households.

In the original study, the authors report randomizing the rollout of the Smartcards across eight districts[6] in the Indian state of Andhra Pradesh between 2010 and 2012. From the

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[4] These are variables measuring the use of Smartcards by participants in the treatment group, labeled as “b17_useSmartcard” and “b26_1_swipeFingerprints”.

[5] The randomization was stratified by districts and socioeconomic characteristics of surveyed households. See Section B of Muralidharan and colleagues (2016, pp.2,907–2,909) for a full description of data collection procedures.

[6] Adilabad, Ananthapur, Kadapa, Khammam, Kurnool, Nalgonda, Nellore and Vizianagaram.

districts, 296 *mandals* (sub-districts) were selected from a total of 405 and randomized into treatment (112 mandals, 37.8%), control (45 mandals, 15.2%) and buffer (139 mandals, 47%) groups.[7] The buffer mandals were excluded from the analysis.[8] In each mandal, a fixed number of villages, known as *gram panchayats* (GPs), were selected, producing a total of 880 GPs. In each GP, 10 households were selected to participate in the survey.

In the original paper, the survey data were analyzed by estimating the following model:

$$Y = \alpha + \beta Treated + District\ FEs + \gamma PC + \delta \bar{Y}^0 + \ error \qquad (1)$$

where $\bar{Y}^0$ is the GP-level mean of the dependent variable at the time of the baseline and *PC* is the principal component (PC) variable that was used to stratify the mandals. The key variable here is *Treated*, which takes a non-zero value if the individual or household belonged to a mandal that had been selected for treatment.

The study employed individual and household beneficiary-level observations for NREGS and SSP programs to conduct intent-to-treat (ITT) analysis, which compares the average outcomes in treatment and control areas. The ITT estimates yield the policy parameter of interest. The implementation of the Smartcard-enabled payment system was assessed on three key policy parameters (Y): payment logistics (i.e. timeliness and ease of access), prevention of leakages and program access.

3.3 Replication results

All replication results are presented in the appendix. The results (Tables A1–A7) from the pure replication exercise are the same as the push-button replication. In addition to the presented replicated findings in the appendix, we report p-values for each estimated coefficient, and they are highlighted in grey in each table. The first table we replicated presents findings on the use of Smartcards for NREGS and SSP programs using the official[9] and survey[10] data. The other results (either original or replicated estimates

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[7] The key difference between the treatment and control group is the system of payments for NREGS and SSP programs. In the treatment group mandals, payments were made through the "Bank → Technology Service Provider (TSP) → Customer Service Provider (CSP) → Worker" Smartcard-enabled channel. The control group payment system channel is from "State → District → Mandal → Gram Panchayat → Worker."

[8] The lag between the deployment of Smartcards in the treatment and control groups was more than two years. Muralidharan and colleagues created the buffer group to avoid contamination of the control group before the mandals in the group were converted to the new payment system and to ensure they had sufficient time to conduct the endline surveys. Through the process, enrollment was allowed to take place in the buffer group without affecting the control mandals.

[9] Muralidharan and colleagues extracted the official records on beneficiary lists and benefits paid from the official disbursement data to determine the official number of Smartcards rolled out and the proportion used to conduct transactions and the amounts disbursed, and to estimate leakages of funds. Leakage is estimated as the difference between the official payment disbursed and the reported actual payment received by the beneficiary during survey.

[10] The survey data are the combination of the baseline and endline household surveys of samples of enrolled beneficiaries in the treatment and control groups. The data include questions on the payment received, participation experience in the NREGS and SSP programs and general socioeconomic information such as income, employment, assets and consumption.

directly associated with Tables A2–A7) use the endline survey data. Tables A2, A3 and A4 reproduce findings on access to payments (i.e. average time taken to collect a payment using the Smartcards), program benefits (effect on leakage) and channels of leakage reduction, respectively. Table A5 reproduces findings on access to programs proxied by participation rates in the NREGS and SSP schemes. The negative and positive effects of the Smartcard implementation, based on opinions of the surveyed beneficiaries, are shown in the reproduction of Muralidharan and colleagues' Table A6. The results of Smartcard implementation by carded and non-carded status are presented in Table A7.

Our replication results are exactly the same as the findings in the original paper. We summarize each of the results presented in the appendix, with additional comments where necessary, in the following sections.

3.3.1 Table A1: official and self-reported use of smartcards

The original results (Table A1) are reasonable and not unexpected, but there is a possibility that the large differences between the official and self-reported use of Smartcards is influenced by the actions of corrupt officials to facilitate leakages of funds. There are more financial incentives for government officials to inflate the records by introducing "ghost" beneficiaries (i.e. workers and pensioners) to divert payments into their personal accounts. Corruption of this nature might keep evolving amid government audit systems, as officials continue to look for ways to manipulate official records to benefit their interests (Afridi and Iversen 2014; Gelb et al. 2018).

When randomization is successful, one expects that there will be no converted villages in the control sample and that all (most) of the villages convert in the treated sample. The official data for NREGS (SSP) payments indicate that 0.5% (0%) of GPs in the non-treatment group have been converted to the Smartcard-based payment system and 0.2% (0%) of the issued cards have been used for transaction by the beneficiaries in those villages. On the other hand, we found more contamination[11] of the treatment group for both programs using the survey data and conduct further investigation in Section 4.

3.3.2 Table A2: access to payments

The results presented in Table A2 are the same as in the original paper, which provides justification of the hypothesis that Smartcards reduce the time for beneficiaries to collect payment for work done or from a pension.

The time gained from the use of Smartcards may be attributed to (i) the new payment delivery mode, which eliminates the use of post offices for payment disbursements, as done in the control group and (ii) the speed of authenticating beneficiaries' identities. Also, the use of Smartcard-enabled payments may have spillover effects through transparency and accountability in reducing the processing time and potential leakages through the post-office payment delivery route if the use of post offices coexists with the biometric system in a mandal to facilitate payments for those without Smartcards in the treatment group. But, if the payment process through the post offices lags behind in terms of efficiency, transparency and accountability over time, then it would encourage more people to enroll to use the biometric cards to benefit from the time savings.

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[11] As Table A8 and A9 show, we further inspect the imbalances in Section 4 (MEA) as outliers.

3.3.3 Table A3: effects on payment amounts and leakages

Muralidharan and colleagues' results presented in Table A3 reveal that the use of Smartcards helps beneficiaries collects more money and reduces incidence of payment leakages. But, we argue that the significant outcomes (i.e. increased payments and reduced leakages) might have been due to transparency and careful verification of the identity of the beneficiaries by the customer service providers in each district. Similarly, the increased earnings could be the result of households' working more days than before, or an NREGS expenditure composition effect, with more of the program resources spent on labor than materials in the surveyed villages.

3.3.4 Table A4: channels of leakage reduction

The results presented in Table A4 reveal that the use of Smartcards reduces the three considered channels of leakages: (i) ghost households (all beneficiaries in the households who were confirmed not to exist or had permanently migrated before the study period started), (ii) over-reporting (job cards that had positive official payments reported but zero survey payments, excluding ghosts) and (iii) bribes to collect or underpayment (bribes paid in order to receive payments).

Muralidharan and colleagues find the effect on the incidence of over-reporting to be the most statistically significant and account for the largest source of leakages. However, we argue that the over-reporting form of leakages could have been possible due to loopholes in the payment delivery route known by the officials and the channeling of money through multiple hands without transparency and accountability, as well as the easy access by corrupt officials to create multiple bank accounts using ghost beneficiaries' names. Such accounts are accessible only by the officials. Afridi and Iversen (2014) describe these types of corruption dynamism as constantly evolving, as officials never stop looking for loopholes in the system for rent-seeking.

3.3.5 Table A5: effects on program access

Muralidharan and colleagues assess the potential effect of leakage reduction driven by the use of Smartcards on beneficiaries' participation rate in the NREGS and SSP programs. The results in the original paper for the program access is the same as our replications results and presented in Table A5.

In all, we agree that the evidence points to the fact that Smartcards does not hinder access to either program in the converted mandals. Also, it is worth noting that the increase in participation could have been driven by increase in demand for workers in the NREGS program, participants' expectation of prompt payments and the incentive officials could gain by enrolling more participants without Smartcards in the same treated areas.

3.3.6 Table A6: beneficiary perceptions of the intervention

Table A6, which is the same as the original results, presents the aggregate opinions of beneficiaries in the converted mandals who had received payments using the old system prior to the introduction of Smartcard-based payments. In addition to the pros and cons of the use of Smartcards highlighted in Table A6, it is clear that the payment authentication system still faces a good deal of criticism and challenges not limited to the high cost of implementation, administrative and political bottlenecks, failure to authenticate genuine beneficiaries after the first attempt and data privacy breaches (Mukhopadhyay et al. 2013; Gelb et al. 2017).

3.3.7 Table A7: Decomposition of treatment effects by carded status

In the treatment mandals where the new payment system has been introduced, there are "carded" GPs (villages that have moved to Smartcard-based payment) and "not carded" GPs (villages that have not yet been converted to the use of Smartcards). In the treated mandals (those that have moved to the biometrically authentication system), there is uneven distribution of Smartcards to beneficiaries in the carded villages.[12] Muralidharan and colleagues examine the effect of Smartcard decomposition based on carded and not carded villages in the treated mandals on payments logistics, leakages and access. The replication results presented in Table A7 are the same as the original results and reveal that there are more gains for beneficiaries with Smartcards in the converted villages than those without Smartcards.

4. Measurement and estimation analyses

This section examines the robustness of the comparable replicated results to changes in model specifications, outliers and alternative estimation method. Of the entire MEA-reported findings, the following subsections discuss only the estimates that differ significantly from the original estimates; the full results are shown in Appendix B.

4.1 MEA I: How does the estimated effect differ as one moves from ITT to TOT?

Muralidharan and colleagues conducted ITT analyses for reasons stated in the last paragraph of Section 2.2. The ITT is used to compare the average outcomes in treatment and control groups. But, they also report "non-experimental decomposition" results in Table A7 by comparing the outcomes within the treatment group where the villages had moved to Smartcard-based payments ("carded GP") and not yet moved to the new payment system ("not carded GP"). Then, we further decomposed using individual beneficiaries' Smartcard status ("have Smartcard, carded GP" or "no Smartcard, carded GP"). The estimated effects at this level can be thought of as estimating the effect of treatment on the treated (TOT), with the caveat that the selection into a treatment group ("Smartcards") was not random. Even though selection into treatment is not random, these estimates are still of interest because they help to establish an upper bound on the benefits of Smartcards.

However, we further explore the TOT analysis by comparing "have Smartcard" to "does not have Smartcard" within carded GPs, as reported in Table B1. This helps understand the benefits of having Smartcards within carded GPs (TOT columns in Table B1) relative to the benefits of converting villages to the Smartcard payments system (ITT columns in Table B1). We used the ordinary least square fixed effect (OLS FE) approach identical to Muralidharan and colleagues' approach for the comparison.

[12] See Tables A8 and A9 for the distribution of Smartcards across districts for the NREGS and SSP programs, respectively.

The reported results in Table B1 show that beneficiaries with Smartcards in carded GPs significantly (i) spend less time to collect payments,[13] (ii) receive more money, (iii) gain reduction in leakage of funds and (iv) experience more access to work, compared to household or individuals without Smartcards in the same carded villages. However, we found no significant difference in the payment lag. These findings, excluding “time to collect,” are consistent with the outcomes from Muralidharan and colleagues’ test of equality between “have Smartcard” and “no Smartcard” in Table A7.

One plausible reason for households with Smartcards having more access to work than those without Smartcards in the same carded villages could be attributed to (i) favoritism (i.e. from close relatives who are among the officials that allocate jobs), (ii) strong local political connections and/or (iii) dissatisfaction and lack of motivation experienced by non-Smartcard holders. For instance, job cardholders without Smartcards can voluntarily demand less work to minimize their loss of earnings due to leakages as an opportunity cost of not using the new payment system.

Our MEA I confirms the robustness of Muralidharan and colleagues’ non-experimental decomposition results (even columns in Table A7) to changes in the decomposition structure as TOT (in Table B1). Unlike the original authors, we provide the average treatment effects by comparing the benefits between having Smartcards and not having Smartcards within the carded GPs, instead of the comparison with the original control group.

4.2 MEA II: Are the original results robust to outliers?

The presence of outliers such as extreme values, if not addressed, can significantly influence and distort the estimated average treatment effects reported in Muralidharan and colleagues (2016). This motivated us to test for outliers and if detected, to test how significantly the outliers influenced the original estimates. Otherwise, the reported results are robust to any form of outliers present in the data set. We use three of the residual-based measures available in Stata for detecting outliers such as (i) discrepancy, which measures the difference between actual and predicted/estimated treatment effects [i.e. $Y - \hat{Y}$]; the closer it is to zero, the more robust are the estimates to outliers; (ii) leverage, which identifies points in the data set where observations on the predictors have multiple extreme values, and their effect on the estimated model; a leverage level with measure greater than 2 K/N will have more effect on the treatment effects compared to low leverage; and (iii) influence, which measures the joint effect of discrepancy and leverage levels of the extreme values on estimated effect; for cases where the outlying values on any of the variables shift the estimated effect by at least $2/\sqrt{N}$ or 1, then the outliers have a high chance of distorting the regression coefficients.

From Tables B2–B7 for corresponding Tables A1–A7 in the original paper (excluding Table A6), none of the outlier measures is found to be above the benchmark values. This indicates that there is no presence of outliers that could distort the estimated average treatment effects in the replicated results (Tables A1–A7). It also implies that the original results are robust to outliers.

[13] This robustness result contradicts Muralidharan and colleagues’ findings. They report in their Table A7, using test of equality, that there is no significant difference in the time taken to collect payment between beneficiaries who have a Smartcard and those without a Smartcard.

4.3 MEA III: Are the original results robust to alternative specification?

The randomizations of the biometrically authenticated payment system across mandals were based on household socioeconomic characteristics. Muralidharan and colleagues control for the variation in socioeconomic characteristics at the mandal level in the estimated regression model (1) by incorporating their first PC as an additional predictor to account for differences in outcomes across each district. PC is a reduced form of a large subset of variables (e.g. socioeconomic characteristics indicators such as income, education and consumption) that are highly correlated and, if simultaneously incorporated in a regression model, might render the estimates biased. The use of PC can help to improve the robustness of a model. On the other hand, there is contention in the literature that PC offers no additional efficiency gain and does not matter if included in a model, compared to when it is excluded. We test this argument to determine whether Muralidharan and colleagues' original results are robust to different variations in the use of a PC variable in the original model.

The authors' descriptive analysis conducted on the baseline household survey data establishes evidence of high multicollinearity. We therefore investigated whether the use of the first PC is more efficient and robust than dropping the PC in modeling the welfare effect of the use of Smartcards. We thus tested the robustness of the PC variable used in the original paper by:

(i) excluding the PC from equation (1) and estimate:

$$Y = \alpha + \beta Treated + \delta \bar{Y}^{0} + District\ FEs + error \qquad (2)$$

The robustness check is to assess the potential weakness associated with PC analysis in the context of this replication study and investigate the robustness of the original results to a different specification of the model without a PC variable, as discussed in the following sub-section.

4.3.1 Exclusion of principal component variable

In Tables B8–B13, the results clearly show that when the PC variable is excluded from the model, the average treatment effects are the same as the original estimates reported in the original paper (Tables A1–A7) for most cases. However, only some estimates (highlighted in yellow) differ very slightly in magnitude from the original average treatment effects by a variation within a range of $\pm$ 2. The signs and statistical significance of the estimated effects are consistent with the original estimates. This implies that the model (1) in the original paper will yield the same policy outcomes if the PC variable is excluded.

Thus, the test for exclusion of the PC variable clearly indicates that there is no potential bias if the original authors decided not to include the first PC series as an additional regressor.

However, these findings (Sections 4.3.1) hindered our attempt to identify household-level characteristics that might contribute to the heterogeneity effect of Smartcards on welfare across surveyed districts. This prompted us to test for heterogeneity as additional robustness checks (Section 5).

4.4 MEA IV: are the original results robust to alternative estimation procedures?

In addition to the specification robustness checks discussed in Section 4.3, we further attempted to test the sensitivity of the original estimates to changes in estimation method. In the original paper, OLS FE was used to estimate each of the policy models. For the purpose of this robustness check, we estimated model (1) using a generalized linear mixed model (GLMM) that accounts for district fixed and random effects, as well as other issues discussed in the replication proposal (Atanda and Reed 2017). The goal was to ascertain the bias that might have been created by linear fixed effect model when the response variables were correlated across clusters (either at the district or mandal level). In other words, we used the GLMM modeling framework to assess the robustness of the estimation method used by Muralidharan and colleagues by controlling for random changes in district- or mandal-specific characteristics. We present the results of this robustness check in Tables B14–B19.

The results reveal that in most of the reported cases estimating the impact of Smartcards on welfare outcomes (e.g. leakages, time taken to collect payments, ease of access to payments), the GLMM estimates are highly comparable and consistent in signs and magnitudes with treatment effects from the original paper, where OLS FE is used. In Tables B14–B18, there are very few exceptional cases (highlighted in yellow) of slight variation in average treatment effects, but the estimates become more significant (e.g. Table B15, columns 5–6; Table B16, Panel B, columns 1–2; Table B17, Panel B, columns 9–10, 11–12); there is slight variation in average treatment effects and the estimates turn out to be insignificant (e.g. Table B16, Panel A, columns 9–10, 11–12; Table B16, Panel B, columns 3–4; Table B17, Panel A, columns 9–10, 11–12; Table B18, columns 13–14, 15–16); and there are different patterns of variations, but the significance of the estimates is comparable in most cases in Table B19.

On the basis of the highlighted differences and comparable estimates, this robustness analysis reveals that Muralidharan and colleagues' original results are less sensitive to the inclusion of random district effects in the model and when estimated with GLMM. In comparison with the OLS FE method, the GLMM produced more significant estimates, but the magnitude of the coefficients were lower in cases where there was slight variation. Therefore, changes in estimation method do not significantly bias the original estimates in Muralidharan and colleagues' paper, giving more credibility to the outcomes from the study in estimating the impact of biometrically authenticated Smartcards payment system in India.

5. Theory of change analysis: can we identify moderating factors that contribute to the heterogeneous effects?

This replication study has clearly verified Muralidharan and colleagues' findings, using the same data set, that biometric authentication technology can improve payment processing time and reduce leakages of funds. The implementation gain from such investment in technology-enabled infrastructure is to improve government service delivery in low- and middle-income countries such as India. Other benefits include improved government efficiency, capability to target the right sets of beneficiaries to match the right welfare programs, transparency and accountability in spending, as well as increased household income and welfare improvement. From the reviewed studies (e.g. Niehaus and Sukhtankar 2013; Muralidharan et al. 2014, 2016; Banerjee et al. 2016; Gelb et al. 2018), it is clear that the mechanism to achieve the gains are the digitized and direct flow of funds (subsidies, transfers and benefits) from the state to the beneficiaries and the verification of beneficiaries' identities using biometric authentication technology like Smartcards. Similar approaches and mechanisms can be adopted by other low- and middlie-income countries. To establish this empirically, we attempted to understand and identify factors that might contribute to the variation in the gains across sampled mandals. Potential factors such as beneficiaries and socioeconomic characteristics within mandals and districts (e.g. age, marital status, income, number of assets, expenditure on food, housing and education, literacy rate, average mandal's per capita income, number of accessible and functioning infrastructures per mandal, poverty rate, household proximity to formal banks by distance) would help to clearly identify and understand the heterogeneity in the gains of using Smartcards across districts. This is expected to provide insights that will help policymakers successfully replicate the programs in other Indian states. Also, other low- and middle-income countries can learn from India's experience and implementation approach, even though the biometric authentication technology still has some challenges (Mukhopadhyay et al. 2013; Gelb et al. 2017).

The motivation for attempting to identify the moderating factors arises from the heterogeneous implementation of the biometrically authenticated payment system across districts that could result in different impacts of the Smartcards. Muralidharan and colleagues (2016, p.2910) note that "there was considerable heterogeneity in the extent of Smartcard coverage across the eight study districts, with average rates ranging from 31 percent in Adilabad to nearly 100 percent in Nalgonda district." To test this, we first introduced an interactive term of treatment and district indicators as control variables in model (1), expressed as:

$$Y = \alpha + \beta Treated + District\ FEs + Treated\ *\ District\ Interaction\ Effects$$
$$+\gamma PC + \delta \bar{Y}^0 +\ error \qquad (3)$$

Then, we tested the joint significance of the interactive term ($Treated *$ $District\ Interaction\ Effects$) as a parameter of interest to determine if the treatment effect is heterogeneous across districts. The results of the hypothesis after estimating model (3) are shown in Tables C1–C6, corresponding to each policy outcome indicators. The p-values from the tested hypotheses reveal no evidence of heterogeneity in the average treatment effects for all of the policy outcomes excluding the following.

Table C1, columns 1–4, indicate heterogeneity in the proportion of villages (GPs) converted to the new payment system and the share of beneficiaries who use the Smartcard for payments. The model was estimated using the official data that the original authors later used for stratification of districts and mandals into different experimental groups. The results from the survey records indicate that the average treatment effect is not heterogeneous.

Table C2, columns 1 and 4, present evidence of heterogeneity in the time it takes beneficiaries to collect payments across districts. This might be due to the large variation in the distance between sampled villages and assigned payment collection centers and the differences in population size. We could not attribute the heterogeneity to socioeconomic factors because the PC estimate in model (3) is not significant in each case.

Table C4, columns 4–6, reveal heterogeneity in the impact of Smartcards on over-reporting and underpayment as channels of leakages for the NREGS program. Similarly, there is insufficient data in the scope of this replication study to directly link the heterogeneity to household socioeconomic factors. Heterogeneous leakages of funds are most likely to be driven by the size of the household and village as a whole. Corrupt officials are more likely to underpay large households and over-report money received by small households in remote villages far from the local council or city. These factors are outside the consideration of this replication study due to unavailable data.

Therefore, we could not identify any moderating factor because of the non-heterogeneity of the treatment effects (in more than 95% of the cases[14]) and the endogeneous nature of the socioeconomic characteristics (identified in Muralidharan et al. 2017). The theory of change analysis reveals that factors which might have contributed to the heterogeneity in payment collection time and leakages of funds in the NREGS program are outside the scope of this replication study and not available from the data set provided by the authors. In cases where they are available, there are multiple missing observations that could have rendered the estimation of heterogeneous effects biased; this supports our argument for the use of the PC variable because of its robustness to missing data.

6. Conclusions

Our replication is exactly comparable to the findings of Muralidharan and colleagues (2016). Using the same large experimental data set and method implemented with “audited codes” in Stata version 14.1 (instead of Stata 10 used by the original authors), we are able to confirm the original findings. This provides strong empirical credibility for the original study for policy inference on the welfare returns of state capacity building (e.g. biometric authentication payment infrastructure) in low- and middle-income countries. This replication study found that Smartcards significantly reduced the time taken to collect payment, reduced leakages of funds and improved the enrollment rate in two welfare programs (employment and pension scheme).

The evidence from our robustness checks as part of the MEA reveals that the original results are comparable in 90 percent of the cases and robust to (i) changes in the non-experimental data structure in estimating the TOT effects, (ii) outliers, (iii) exclusion of PC variable from the estimated model and (iv) inclusion of district random effect and changes to the estimation method. The average treatment effects from OLS FE and GLMM estimation are comparable, but there are a few cases in which GLMM produces estimates that are more significant, while treatment effects from the original method remain insignificant.

[14] In the other cases where heterogeneity exists, the PC variable in model (4) was insignificant.

Despite the comparable results and robustness of the original estimates from this replication, we couldn't perform a further test that involves replacing the PC variable with selected household socioeconomic characteristics because of the endogeneity nature of the variables (see Muralidharan et al. 2017 for more details) and lots of missing observations in the socioeconomic data set. Also, the hypotheses that test the heterogeneity in treatment effects across districts are rejected for nearly all the policy outcomes that measure the importance of Smartcards on welfare. Therefore, the biases created by the non-heterogeneity of the treatment effects limit our attempt to identify the moderating factors that might have contributed to differences in average treatment effects across districts.

We thus conclude that the original results are comparable to the replicated findings and robust to different model specifications and estimation method. In addition to the verification exercise, this replication study has established that the effect of Smartcards on welfare outcomes (e.g. leakages, time taken to collect payments, ease of access to payments) across the eight surveyed districts in the Indian state of Andhra Pradesh is not statistically heterogeneous. However, the rollout of the biometrically authenticated payment system across all the districts is heterogeneous – i.e. heterogeneity in Smartcard implementation does not equate to heterogeneity of its impact on welfare across the surveyed districts.

However, this replication study has provided sufficient verifiable evidence that could be useful for policymakers in other low- and middle-income countries to justify and consider the use of Smartcards for the distribution of funds (benefits, transfers and subsidies) to reduce poverty, target beneficiaries and improve government service delivery. The key policy implications from this study are in threefold. First, Smartcards can help policymakers and donors directly reach targeted beneficiaries in a timely manner and without intermediaries, who might be corrupt and cause leakages of funds. Second, lessons from the implementation of the Smartcard-based payments infrastructure can help policymakers design efficient and validated blueprints for achieving some of the Sustainable Development Goals, such as No Poverty (Goal 1), Zero Hunger (Goal 2), Gender Equality (Goal 5), Decent Work and Economic Growth (Goal 8), Reduced Inequalities (Goal 10), Strong Institutions (Goal 16) and Global Partnerships for the Goals (Goal 17). Finally, policymakers can maximize returns on such technology by using it to authenticate the identity of genuine beneficiaries for non-financial welfare packages, such as liquefied natural gas cylinders, food (Gelb et al. 2017) and potable water in regions experiencing severe drought, malnutrition and resource crises.

Appendix A: Pure replication results

Table A1: Official and self-reported use of Smartcards

	Official data		Survey data	
	Carded GP	Mean fraction carded payments	Payments generally carded (village mean)	Most recent payment carded (village mean)
	(1)	(2)	(3)	(4)
Panel A: NREGS				
Treatment	0.67	0.45	0.38	0.38
	(0.045)	(0.041)	(0.043)	(0.042)
p-value	< 0.001	< 0.001	< 0.001	< 0.001
District FE	Yes	Yes	Yes	Yes
Adj R-squared	0.45	0.48	0.36	0.36
Control mean	0.0046	0.0017	0.039	0.013
No. of cases	880	880	818	818
Level	GP	GP	GP	GP
Panel B: SSP				
Treatment	0.79	0.59	0.45	0.45
	(0.042)	(0.038)	(0.052)	(0.049)
p-value	< 0.001	< 0.001	< 0.001	< 0.001
District FE	Yes	Yes	Yes	Yes
Adj R-squared	0.57	0.57	0.38	0.38
Control mean	0	0	0.069	0.044
No. of cases	880	880	878	878
Level	GP	GP	GP	GP

Note: Standard errors clustered at mandal level in parentheses; the grey-highlighted rows (p-values) are values we added to the original results.

Table A2: Access to payments

	Time to collect				Avg. payment lag (days)		Abs. payment lag deviation (days)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	–22	–22	–6.1	–3.5	–5.8	–10	–2.5	–4.7
	(9.2)	(8.7)	(5.2)	(5.4)	(3.5)	(3.5)	(0.99)	(1.6)
p-value	0.019	0.014	0.244	0.521	0.094	0.005	0.014	0.004
BL GP mean		0.079		0.23		0.013		0.042
		(0.041)		(0.07)		(0.08)		(0.053)
p-value		0.057		0.001		0.869		0.429
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	No	No	No	No	Yes	Yes	Yes	Yes
Adj R-squared	0.06	0.08	0.07	0.11	0.17	0.33	0.08	0.17
Control mean	112	112	77	77	34	34	12	12
No. of cases	10191	10120	3789	3574	14213	7201	14213	7201
Level	Indiv.	Indiv.	Indiv.	Indiv.	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week
Survey	NREGS	NREGS	SSP	SSP	NREGS	NREGS	NREGS	NREGS

Note: BL – Base line; Standard errors clustered at mandal level in parentheses; the grey-highlighted rows (p-values) are values we added to the original results.

Table A3: Official and survey reports of program benefits

	Official		Survey		Leakage	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: NREGS						
Treatment	11	9.6	35	35	–24	–25
	(12)	(12)	(16)	(16)	(13)	(13)
p-value	0.347	0.425	0.026	0.025	0.067	0.054
BL GP mean		0.13				
		(0.027)		(0.037)		(0.038)
p-value		< 0.001		0.003		0.014
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.03	0.05	0.05	0.06	0.04	0.04
Control mean	127	127	146	146	–20	–20
N. of cases	5143	5107	5143	5107	5143	5107
Panel B: SSP						
Treatment	4.3	5.1	12	12	–7.5	7
	(5.3)	(5.4)	(5.9)	(6.1)	(3.9)	(3.9)
p-value	0.415	0.35	0.045	0.052	0.053	0.079
BL GP mean		0.16		0.0074		–0.022
		(0.092)		(0.022)		(0.026)
p-value		0.088		0.733		0.413
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0	0.01	0.01	0.01	0.01	0.01
Control mean	251	251	236	236	15	15
No. of cases	3330	3135	3330	3135	3330	3135

Note: Standard errors clustered at mandal level in parentheses; the grey-highlighted rows (p-values) are values we added to the original results.

Table A4: Illustrating channels of leakage reduction

	Ghost households (%)		Other over-reporting (%)		Bribe to collect (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: NREGS						
Treatment	–0.0095	–0.0091	–0.082	–0.084	–0.0035	–0.0036
	(0.02)	(0.021)	(0.033)	(0.036)	(0.0085)	(0.0085)
p-value	0.645	0.665	0.014	0.02	0.678	0.669
BL GP mean		–0.017		0.016		0.000041
		(0.067)		(0.044)		(0.000041)
p-value		0.798		0.721		0.325
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.02	0.02	0.05	0.04	0.01	0.01
Control mean	0.11	0.11	0.26	0.26	0.021	0.021
No. of cases	5278	5242	3953	3672	10375	10304
Level	HH	HH	HH	HH	Indiv.	Indiv.
Panel B: SSP						
Treatment	–2.9	–2.4	–2.7	–3.1	–2.3	–2.4
	(2.7)	(2.7)	(2.9)	(3)	(1.9)	(2)
p-value	0.278	0.376	0.358	0.293	0.224	0.235
BL GP mean		0.19		0.024		–0.02
		(0.16)		(0.01)		(0.045)
p-value		0.233		0.022		0.657
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.01	0.01	0.01	0.01	0.01	0.01
Control mean	11	11	1.7	1.7	2.5	2.5
No. of cases	3330	3135	3165	2986	3165	2986

Note: Standard errors clustered at mandal level in parentheses; the grey-highlighted rows (p-values) are values we added to the original results.

Table A5: Access to programs

	Proportion of HH doing NREGS work		Was any HH member unable to get NREGS work in		Is NREGS work available when anyone wants it?		Did you have to pay anything to get this NREGS work?		Did you have to pay anything to start receiving this pension?	
	Study period	Study period	May	January	All Months	All months	NREGS	NREGS	SSP	SSP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	0.072	0.071	–0.023	–0.027	0.027	0.024	–0.0003	–0.00054	–0.046	–0.055
	(0.033)	(0.033)	(0.027)	(0.033)	(0.015)	(0.015)	(0.0015)	(0.0015)	(0.031)	(0.039)
p-value	0.03	0.034	0.398	0.41	0.079	0.119	0.84	0.719	0.137	0.159
BL GP mean		0.14				–0.023		–0.0064		0.025
		(0.038)				(0.027)		(0.0031)		(0.046)
p-value		< 0.001				0.407		0.043		0.585
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.05	0.06	0.1	0.11	0.02	0.02	0	0	0.05	0.05
Control mean	0.42	0.42	0.2	0.42	0.035	0.035	0.0022	0.0022	0.075	0.075
No. of cases	4943	4909	4748	4496	4755	4715	7185	6861	581	352
Level	HH	HH	HH	HH	HH	HH	Indiv.	Indiv.	Indiv.	Indiv.

Note: Standard errors clustered at mandal level in parentheses; the grey-highlighted rows (p-values) are values we added to the original results.

Table A6: Beneficiary opinions of Smartcards

	NREGS				SSP			
	Agree	Disagree	Neutral/ Don't know	N	Agree	Disagree	Neutral/ Don't know	N
Positives:								
• Smartcards increase speed of payments (less wait times)	0.83	0.4	0.13	3336	0.87	0.07	0.06	1451
• With a Smartcard, I make fewer trips to receive my payments	0.78	0.4	0.18	3334	0.83	0.04	0.12	1450
• I have a better chance of getting the money I am owed by using a Smartcard	0.83	0.01	0.16	3333	0.86	0.03	0.11	1450
• Because I use a Smartcard, no one can collect a payment on my behalf	0.82	0.02	0.16	3331	0.86	0.03	0.11	1446
Negatives:								
• It was difficult to enroll to obtain a Smartcard	0.19	0.66	0.15	3338	0.29	0.6	0.11	1451
• I'm afraid of losing my Smartcard and being denied payment	0.63	0.15	0.21	3235	0.71	0.15	0.14	1403
• When I go to collect a payment, I am afraid that the payment reader will not work	0.6	0.18	0.22	3237	0.67	0.18	0.14	1403
• I would trust the Smartcard system enough to deposit money in my Smartcard account	0.29	0.41	0.3	3334	0.31	0.46	0.24	1448
Overall:								
Do you prefer the Smartcard over the old system of payments?	0.9	0.03	0.07	3346	0.93	0.03	0.04	1454

Note: Standard errors clustered at mandal level in parentheses.

Table A7: Nonexperimental decomposition of treatment effects by carded status

	Time to collect		Payment lag		Survey				Leakage				Proportion of HHs doing NREGS work	
	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	SSP	SSP	NREGS	NREGS	SSP	SSP	NREGS	NREGS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Carded GP	–33		–5		37		14		–30		–4.5		0.063	
	(8.1)		(2.8)		(17)		(6.2)		(15)		(4.4)		(0.036)	
p-value	< 0.001		0.081		0.030		0.025		0.044		0.299		0.078	
Have Scard, carded GP		–33		–4.4		152		24		–71		–12		0.25
		(8.4)		(3)		(24)		(7.1)		(23)		(4.7)		(0.043)
p-value		< 0.001		0.146		0.000		0.001		0.002		0.014		0.000
No Scard, carded GP		–33		–5.9		–55		–2.2		3.1		7.1		–0.12
		(8.6)		(2.8)		(17)		(9.9)		(14)		(6.2)		(0.044)
p-value		< 0.001		0.040		0.001		0.820		0.820		0.255		0.008
Not carded GP	4.9	4.9	–7.4	–7.5	22	19	8.3	7.7	–13	–12	–12	–12	0.064	0.056
	(13)	(13)	(5)	(5)	(26)	(26)	(9.6)	(9.6)	(21)	(21)	(5.8)	(5.8)	(0.044)	(0.047)
p-value	0.704	0.708	0.136	0.131	0.385	0.454	0.386	0.426	0.540	0.576	0.036	0.044	0.149	0.231
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	No	No	Yes	Yes	No	No	No	No	No	No	No	No	No	No
BL GP mean	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-values (test of equality):														
Carded GP = not carded GP	< 0.001		0.45		0.5		0.54		0.38		0.21		0.98	
Have SC = No SC		0.88		0.37		< 0.001		0.017		< 0.001		0.0028		< 0.001
Adj R-squared	0.1	0.1	0.17	0.17	0.06	0.11	0.0063	0.0093	0.044	0.052	0.0085	0.013	0.054	0.11
Control mean	112	112	34	34	166	166	236	236	–22	–22	15	15	0.48	0.48
No. of cases	10120	10086	14165	14165	4915	4915	3131	3131	4915	4915	3131	3131	4717	4717
Level	Indiv.	Indiv.	Indiv-Week	Indiv-Week	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH

Note: Standard errors clustered at mandal level in parentheses; the grey-highlighted rows (p-values) are values we added to the original results.

Table A8: Number of participants across surveyed districts for the NREGS program

Identifier	6	92	132	149	151	334	491	503	
	District 1	District 2	District 3	District 4	District 5	District 6	District 7	District 8	TOTAL
Distinct/Unique per district									
Mandals	14	21	17	21	21	21	21	21	157
GP	26	29	19	22	21	25	25	24	191
Job cardholders: NREGS	301	669	336	660	650	705	698	698	4717
Households	301	669	336	660	650	705	698	698	4717
Individuals across all HHs									
Observation (indv)	671	1449	708	1659	1510	1580	1425	1445	10447
Treatment = 1	457	1063	516	1207	1119	1119	1037	1001	7519
Treatment = 0	214	386	192	452	391	461	388	444	2928
Have Smartcard = 1	258	275	368	784	584	29	0	209	2507
Have Smartcard = 0	332	460	164	357	523	767	0	267	2870
Have Smartcard = (missing)	81	714	176	518	403	784	1425	969	5070
Treatment = 1 & have Smartcard = 1	228	241	305	586	488	29	0	137	2014
Treatment = 1 & have Smartcard = 0	173	380	109	280	334	622	0	254	2152
Treatment = 1 & have Smartcard = . (missing)	56	442	102	341	297	468	1037	610	3353
Treatment = 0 & have Smartcard = 1	30	34	63	198	96	0	0	72	493
Treatment = 0 & have Smartcard = 0	159	80	55	77	189	145	0	13	718
Treatment = 0 & have Smartcard = . (missing)	25	272	74	177	106	316	388	359	1717
Carded GP = 1	230	660	503	934	619	402	1037	825	5210
Carded GP = 0	441	789	205	725	891	1178	388	620	5237
Treatment = 1 & carded GP = 1	230	660	503	934	619	385	1037	810	5178
Treatment = 1 & carded GP = 0	227	403	13	273	500	734	0	191	2341

Identifier	6	92	132	149	151	334	491	503	
	District 1	District 2	District 3	District 4	District 5	District 6	District 7	District 8	TOTAL
Treatment = 0 & carded GP = 1	0	0	0	0	0	17	0	15	32
Treatment = 0 & carded GP = 0	214	386	192	452	391	444	388	429	2896
Treated, have Smartcard, carded GP	173	176	305	556	362	24	0	128	1724
Treated, have Smartcard, uncarded GP	55	65	0	30	126	5	0	9	290
Treated, no Smartcard, carded GP	42	220	109	210	158	228	0	214	1181
Treated, no Smartcard, uncarded GP	131	160	0	70	176	394	0	40	971
Untreated, have Smartcard, carded GP	0	0	0	0	0	0	0	14	14
Untreated, have Smartcard, uncarded GP	30	34	63	198	96	0	0	58	479
Untreated, no Smartcard, carded GP	0	0	0	0	0	6	0	0	6
Untreated, no Smartcard, uncarded GP	159	80	55	77	189	139	0	13	712
Treated, Smartcard (missing obs.), carded GP	15	264	89	168	99	133	1037	468	2273
Treated, Smartcard (missing obs.), uncarded GP	41	178	13	173	198	335	0	142	1080
Untreated, Smartcard (missing obs.), carded GP	0	0	0	0	0	11	0	1	12
Untreated, Smartcard (missing obs.), uncarded GP	25	272	74	177	106	305	388	358	1705

Table A9: Number of participants across surveyed districts for the SSP program

Identifier	6	92	132	149	151	334	491	503	
	District 1	District 2	District 3	District 4	District 5	District 6	District 7	District 8	TOTAL
Distinct/Unique per district									
Mandals	14	21	17	21	21	21	21	21	157
GP	26	29	19	22	21	25	25	24	191
Households	208	459	220	458	460	452	460	445	3162
Individuals across all households									
Observation (indv)	269	540	259	563	541	576	557	527	3832
Treatment = 1	197	388	184	404	384	418	398	377	2750
Treatment = 0	72	152	75	159	157	158	159	150	1082
Have Smartcard = 1	109	220	138	300	271	39	2	114	1193
Have Smartcard = 0	106	146	47	119	145	347	0	142	1052
Have Smartcard = (missing)	54	174	74	144	125	190	555	271	1587
Treatment = 1 & have smartcard = 1	99	203	127	223	216	38	2	79	987
Treatment = 1 & have smartcard = 0	61	110	27	85	79	305	0	137	804
Treatment = 1 & have smartcard = . (missing)	37	75	30	96	89	75	396	161	959
Treatment = 0 & have Smartcard = 1	10	17	11	77	55	1	0	35	206
Treatment = 0 & have Smartcard = 0	45	36	20	34	66	42	0	5	248
Treatment = 0 & have Smartcard = . (missing)	17	99	44	48	36	115	159	110	628
Carded GP = 1	99	238	184	293	204	149	398	310	1875
Carded GP = 0	170	302	75	270	337	427	159	217	1957
Treatment = 1 & carded GP = 1	99	238	184	293	204	145	398	306	1867
Treatment = 1 & carded GP = 0	98	150	0	111	180	273	0	71	883

Identifier	6	92	132	149	151	334	491	503	
	District 1	District 2	District 3	District 4	District 5	District 6	District 7	District 8	TOTAL
Treatment = 0 & carded GP = 1	0	0	0	0	0	4	0	4	8
Treatment = 0 & carded GP = 0	72	152	75	159	157	154	159	146	1074
Treated, have Smartcard, carded GP	75	135	127	204	144	23	2	64	774
Treated, have Smartcard, uncarded GP	24	68	0	19	72	15	0	15	213
Treated, no Smartcard, carded GP	20	60	27	58	34	99	0	113	411
Treated, no Smartcard, uncarded GP	41	50	0	27	45	206	0	24	393
Untreated, have Smartcard, carded GP	0	0	0	0	0	0	0	4	4
Untreated, have Smartcard, uncarded GP	10	17	11	77	55	1	0	31	202
Untreated, no Smartcard, carded GP	0	0	0	0	0	1	0	0	1
Untreated, no Smartcard, uncarded GP	45	36	20	34	66	41	0	5	247
Treated, Smartcard (missing obs.), carded GP	4	43	30	31	26	23	396	129	682
Treated, Smartcard (missing obs.), uncarded GP	33	32	0	65	63	52	0	32	277
Untreated, Smartcard (missing obs.), carded GP	0	0	0	0	0	3	0	0	3
Untreated, Smartcard (missing obs.), uncarded GP	17	99	44	48	36	112	159	110	625

Appendix B: Measurement and estimation analyses

MEA I: How does the estimated effect differ as one moves from ITT to TOT?

Table B1: MEA I – nonexperimental decomposition of treatment effects by carded status within treatment group

	Time to collect		Payment lag		Survey				Leakage				Proportion of HHs doing NREGS work	
	ITT	TOT	ITT	TOT	ITT	TOT	ITT	TOT	ITT	TOT	ITT	TOT	ITT	TOT
	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	SSP	SSP	NREGS	NREGS	SSP	SSP	NREGS	NREGS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Carded GP	–33	–12	–5	0.25	37	189	14	27	–30	–72	–4.5	–9	0.063	0.320
	(8.1)	(6.7)	(2.8)	(1.08)	(17)	(22)	(6.2)	(9)	(15)	(22)	(4.4)	(5.60)	(0.036)	(0.05)
p-value	< 0.001	0.071	0.081	0.819	0.030	< 0.001	0.025	0.004	0.044	0.001	0.299	0.131	0.078	< 0.001
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	No	No	Yes	Yes	No	No	No	No	No	No	No	No	No	No
BL GP mean	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.1	0.09	0.17	0.17	0.06	0.11	0.0063	0.0092	0.044	0.0523	0.0085	0.0035	0.054	0.129
Control mean	112	97	34	23	166	144	236	240	–22	–26	15	10	0.48	0.44
No. of cases	10120	7294	14165	10383	4915	3545	3131	2219	4915	3545	3131	2219	4717	3406
Level	Indiv.	Indiv.	Indiv-Week	Indiv-Week	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH

Note: The grey-highlighted row (p-values) are values we added to the original results.

Are the results robust?

MEA II: outliers

Table B2: MEA II – official and self-reported use of Smartcards

Outlier measures	Official data				Survey data			
	Carded GP		Mean fraction carded payments		Payments generally carded (village mean)		Most recent payment carded (village mean)	
	NREGS	SSP	NREGS	SSP	NREGS	SSP	NREGS	SSP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Discrepancy	4.59E-05	9.51E-06	–8.87E-06	0.0000241	1.01E-05	5.97E-05	3.94E-05	0.0000607
Leverage	0.011364	0.0113636	0.011364	0.0113636	0.012225	0.01139	0.012225	0.0113895
Influence	–5.11E-06	–2.29E-05	9.67E-06	–1.85E-05	5.36E-06	–3.21E-06	1.48E-05	2.53E-06
No. of cases	880	880	880	880	878	878	878	878

Table B3: MEA II – access to payments

Outlier measures	Time to collect				Avg. payment lag (days)		Abs. payment lag deviation (days)	
	NREGS	NREGS	SSP	SSP	NREGS	NREGS	NREGS	NREGS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Discrepancy	–1.63E-07	–2.38E-05	5.91E-06	–0.000188	–2.21E-06	–9.94E-06	2.51E-06	–6.62E-06
Leverage	0.000981	0.001087	0.002639	0.0030778	0.00137	0.002941	0.00137	0.0029294
Influence	–6.10E-07	–1.94E-07	1.76E-06	–2.17E-07	–2.59E-07	–6.21E-07	–2.16E-07	–4.62E-07
No. of cases	10191	10120	3789	3574	14213	7201	14213	7201

Table B4: MEA II – official and survey reports of program benefits

Outlier measures	Official		Survey		Leakage	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: NREGS			
Discrepancy	–4.69E-07	–9.41E-07	–5.77E-06	–2E-05	5.63E-06	5.43E-06
Leverage	0.001944	0.002154	0.001944	0.002154	0.001944	0.002154
Influence	1.23E-07	1.40E-07	–1.40E-08	4.00E-07	–2.98E-07	–4.77E-08
N. of cases	5143	5107	5143	5107	5143	5107
			Panel B: SSP			
Discrepancy	–9.76E-07	–7.35E-06	1.76E-06	–2.4E-05	–4.69E-06	8.38E-05
Leverage	0.003003	0.003509	0.003003	0.003509	0.003003	0.003509
Influence	4.07E-07	1.96E-07	4.78E-07	–5.35E-07	–3.06E-06	8.12E-09
No. of cases	3330	3135	3330	3135	3330	3135

Table B5: MEA II – illustrating channels of leakage reduction

Outlier measures	Ghost households (%)		Other over-reporting (%)		Bribe to collect (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: NREGS					
Discrepancy	–2.76E-06	–3.54E-06	1.57E-05	9.66E-06	1.00E-06	–1.72E-06
Leverage	0.001895	0.002098	0.002547	0.003024	0.000964	0.001067
Influence	–2.49E-07	–9.52E-08	8.02E-07	5.85E-07	–3.30E-08	–5.84E-08
N. of cases	5278	5242	3953	3672	10375	10304
	Panel B: SSP					
Discrepancy	–2.85E-06	–2.14E-05	–2.68E-06	2.56E-05	–5.43E-06	2.36E-06
Leverage	0.003003	0.003509	0.003164	0.003705	0.003164	0.003672
Influence	–2.72E-06	–2.86E-06	–4.50E-07	–2.26E-06	–7.63E-04	–8.02E-04
No. of cases	3330	3135	3165	2986	3165	2986

Table B6: MEA II – access to programs

Outlier measures	Proportion of HHs doing NREGS work		Was any HH member unable to get NREGS work in		Is NREGS work available when anyone wants it?		Did you have to pay anything to get this NREGS work?		Did you have to pay anything to start receiving this pension?	
	Study period	Study period	May	January	All months	All months	NREGS	NREGS	SSP	SSP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Discrepancy	–7.74E-06	–1.3E-05	6.63E-06	1.22E-06	1.38E-06	5.29E-06	–1.92E-06	–7.27E-08	–9.7E-05	–0.0002
Leverage	0.002023	0.002241	0.002111	0.002229	0.002108	0.002339	0.001401	0.00158	0.01826	0.033157
Influence	–3.08E-07	–2.60E-07	5.36E-08	4.27E-07	2.04E-07	1.59E-07	2.35E-06	2.07E-06	–3.1E-05	–7.6E-05
No. of cases	4943	4909	4748	4496	4755	4715	7185	6861	581	352

Table B7: MEA II – nonexperimental decomposition of treatment effects by carded status

Outlier measures	Time to collect		Payment lag		Survey		
	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	SSP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Discrepancy	–2.3E-05	–2.2E-05	–2.26E-06	–1.99E-06	–1.8E-05	–2.4E-05	–2.26E-05
Leverage	0.001187	0.001291	0.001458	0.001543	0.002442	0.002645	0.003833
Influence	–4.52E-07	–6.03E-07	–2.66E-07	–1.76E-07	1.41E-07	4.28E-07	–1.63E-07
No. of cases	10120	10086	14165	14165	4915	4915	3131

Outlier measures	Survey	Leakage				Proportion of HHs doing NREGS work	
	SSP	NREGS	NREGS	SSP	SSP	NREGS	NREGS
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Discrepancy	–3E-05	6.82E-06	9.07E-06	0.000082	8.76E-05	–1.3E-05	–2.3E-05
Leverage	0.004152	0.002442	0.002645	0.003833	0.004152	0.002544	0.002756
Influence	4.56E-07	–2.62E-07	–8.48E-07	–2.35E-07	–1.35E-06	–2.80E-07	–3.50E-07
No. of cases	3131	4915	4915	3131	3131	4717	4717

MEA III: alternative specifications

Table B8: MEA III – official and self-reported use of Smartcards

	Official data				Survey data			
	Carded GP		Mean fraction carded payments		Payments generally carded (village mean)		Most recent payment carded (village mean)	
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: NREGS								
Treatment	0.67	0.67	0.45	0.45	0.38	0.37	0.38	0.37
	(0.045)	(0.045)	(0.041)	(0.041)	(0.043)	(0.043)	(0.042)	(0.042)
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.45	0.45	0.48	0.49	0.36	0.37	0.36	0.36
Control mean	0.0046	0.0046	0.0017	0.0017	0.039	0.039	0.013	0.013
No. of cases	880	880	880	880	818	818	818	818
Level	GP	GP	GP	GP	GP	GP	GP	GP
Panel B: SSP								
Treatment	0.79	0.79	0.59	0.59	0.45	0.45	0.45	0.45
	(0.042)	(0.041)	(0.038)	(0.037)	(0.052)	(0.052)	(0.049)	(0.049)
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.57	0.58	0.57	0.57	0.38	0.39	0.38	0.39
Control mean	0	0	0	0	0.069	0.069	0.044	0.044
No. of cases	880	880	880	880	878	878	878	878
Level	GP	GP	GP	GP	GP	GP	GP	GP

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B9: MEA III – access to payments

	Time to collect							
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	–22	–21	–22	–21	–6.1	–5.8	–3.5	–2.9
	(9.2)	(9.3)	(8.7)	(8.7)	(5.2)	(5.3)	(5.4)	(5.6)
p-value	0.019	0.024	0.014	0.015	0.244	0.282	0.521	0.604
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	No	No	No	No	No	No	No	No
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes
Adj R-squared	0.06	0.06	0.08	0.08	0.07	0.07	0.11	0.11
Control mean	112	112	112	112	77	77	77	77
No. of cases	10191	10191	10120	10120	3789	3789	3574	3574
Level	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.
Survey	NREGS	NREGS	NREGS	NREGS	SSP	SSP	SSP	SSP
	Avg. payment lag (days)				Abs. payment lag deviation (days)			
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treatment	–5.8	–7.1	–10	–10	–2.5	–2.9	–4.7	–4.7
	(3.5)	(3.8)	(3.5)	(3.6)	(0.99)	(1.06)	(1.6)	(1.5)
p-value	0.094	0.067	0.005	0.005	0.014	0.006	0.004	0.003
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes
Adj R-squared	0.17	0.14	0.33	0.31	0.08	0.07	0.17	0.17
Control mean	34	34	34	34	12	12	12	12
No. of cases	14213	14213	7201	7201	14213	14213	7201	7201
Level	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week
Survey	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B10: MEA III – official and survey reports of program benefits

	Official				Survey				Leakage			
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: NREGS												
Treatment	11	10	9.6	8	35	36	35	36	–24	–26	–25	–27
	(12)	(12)	(12)	(12)	(16)	(15)	(16)	(15)	(13)	(13)	(13)	(13)
p-value	0.347	0.391	0.425	0.507	0.026	0.02	0.025	0.02	0.067	0.047	0.054	0.035
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Adj. R-squared	0.03	0.04	0.05	0.05	0.05	0.05	0.06	0.06	0.04	0.04	0.04	0.04
Control mean	127	127	127	127	146	146	146	146	–20	–20	–20	–20
N. of cases	5143	5143	5107	5107	5143	5143	5107	5107	5143	5143	5107	5107
Panel B: SSP	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
Treatment	4.3	4.1	5.1	4.9	12	12	12	12	–7.5	–7.8	7	7
	(5.3)	(5.5)	(5.4)	(5.6)	(5.9)	(6)	(6.1)	(6.2)	(3.9)	(3.9)	(3.9)	(4)
p-value	0.415	0.452	0.350	0.382	0.045	0.047	0.052	0.054	0.053	0.046	0.079	0.067
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Adj. R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Control mean	251	250	251	250	236	236	236	236	15	15	15	15
No. of cases	3330	3330	3135	3135	3330	3330	3135	3135	3330	3330	3135	3135

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B11: MEA III – illustrating channels of leakage reduction

	Ghost households (%)				Other over-reporting (%)				Bribe to collect (%)			
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: NREGS												
Treatment	–0.0095	–0.0112	–0.0091	–0.0118	–0.082	–0.082	–0.084	–0.082	–0.0035	–0.0021	–0.0036	–0.0021
	(0.020)	(0.020)	(0.021)	(0.021)	(0.033)	(0.033)	(0.036)	(0.036)	(0.0085)	(0.0088)	–0.0085	(0.0088)
p-value	0.645	0.559	0.665	0.568	0.014	0.014	0.020	0.023	0.678	0.678	0.669	0.808
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Adj. R-squared	0.02	0.02	0.02	0.02	0.05	0.05	0.04	0.05	0.01	0.01	0.01	0.01
Control mean	0.11	0.11	0.11	0.11	0.26	0.26	0.26	0.26	0.021	0.021	0.021	0.021
No. of cases	5278	5278	5242	5242	3953	3953	3672	3672	10375	10375	10304	10304
Level	HH	HH	HH	HH	HH	HH	HH	HH	Indiv.	Indiv.	Indiv.	Indiv.
Panel B: SSP												
Treatment	–2.9	–2.7	–2.4	–2.1	–2.7	–3.2	–3.1	–3.7	–2.3	–2.3	–2.4	–2.4
	(2.7)	(2.6)	(2.7)	(2.7)	(2.9)	(3.1)	(3.0)	(3.2)	(1.9)	(1.9)	(2.0)	(2.0)
p-value	0.278	0.314	0.376	0.421	0.358	0.304	0.293	0.247	0.224	0.224	0.235	0.234
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Adj. R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Control mean	11	11	11	11	1.7	1.7	1.7	1.7	2.5	2.5	2.5	2.5
No. of cases	3330	3330	3135	3135	3165	3165	2986	2986	3165	3165	2986	2986

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B12: MEA III – access to programs

	Proportion of HHs doing NREGS work				Was any HH member unable to get NREGS work in				Is NREGS work available when anyone wants it?	
	Study period	Study period	Study period	Study period	May	May	January	January	All months	All months
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	0.072	0.076	0.071	0.075	–0.023	–0.025	–0.027	–0.033	0.027	0.026
	(0.033)	(0.033)	(0.033	(0.033)	(0.027)	(0.027)	(0.033)	(0.033)	(0.015)	(0.015)
p-value	0.03	0.02	0.034	0.025	0.398	0.366	0.41	0.41	0.079	0.081
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Adj. R-squared	0.05	0.05	0.06	0.06	0.1	0.1	0.11	0.11	0.02	0.02
Control mean	0.42	0.42	0.42	0.42	0.20	0.27	0.42	0.42	0.035	0.035
No. of cases	4943	4943	4909	4909	4748	4748	4496	4496	4755	4755
Level	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
	Is NREGS work available when anyone wants it?		Did you have to pay anything to get this NREGS work?				Did you have to pay anything to start receiving this pension?			
	All months	All months	NREGS	NREGS	NREGS	NREGS	SSP	SSP	SSP	SSP
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Treatment	0.024	0.024	–0.0003	–0.0001	–0.00054	–0.00037	–0.046	–0.046	–0.055	–0.055
	(0.015)	(0.015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.031)	(0.031)	(0.039)	(0.039)
p-value	0.119	0.112	0.840	0.918	0.719	0.806	0.137	0.139	0.159	0.160
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BL GP mean	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Adj. R-squared	0.02	0.02	0.002	0.002	0.001	0.001	0.05	0.06	0.05	0.08
Control mean	0.035	0.035	0.0022	0.0022	0.0022	0.0022	0.075	0.075	0.075	0.075
No. of cases	4715	4715	7185	7185	6861	6861	581	581	352	352
Level	HH	HH	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B13: MEA III – nonexperimental decomposition of treatment effects by carded status

	Time to collect				Payment lag				Survey					
	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	SSP	SSP
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Carded GP	–33	–32			–5	–7			37	38			14	14
	(8.1)	(8.1)			(2.8)	(3.2)			(17)	(17)			(6.2)	(6.2)
p-value	< 0.001	< 0.001			0.081	0.081			0.03	0.03			0.025	0.025
Have Scard, carded GP			–33	–33			–4.4	–6			152	152		
			(8.4)	(8.5)			(3)	(3)			(24)	(24)		
p-value			< 0.001	< 0.001			0.146	0.073			< 0.001	< 0.001		
No Scard, carded GP			–33	–32			–5.9	–7.8			–55	–55		
			(8.6)	(8.6)			(2.8)	(3.2)			(17)	(17)		
p-value			< 0.001	< 0.001			0.04	0.017			0.001	0.002		
Not carded GP	4.9	5.1	4.9	5	–7.4	–7.9	–7.5	–8	22	22	19	20	8.3	8.4
	(13)	(13)	(13)	(13)	(5)	(5)	(5)	(5)	(26)	(26)	(26)	(26)	(9.6)	(9.8)
p-value	0.704	0.697	0.708	0.702	0.136	0.148	0.131	0.131	0.385	0.380	0.454	0.450	0.386	0.390
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No	No	No
BL GP mean	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
p-values (test of equality):														
Carded GP = not carded GP	< 0.001	< 0.001			0.45	0.72			0.5	0.5			0.54	0.54
Have SC = no SC			0.88	0.88			0.37	0.33			< 0.001	< 0.001		
Adj R-squared	0.1	0.1	0.1	0.1	0.17	0.14	0.17	0.14	0.06	0.06	0.11	0.11	0.0063	0.0098
Control mean	112	112	112	112	34	34	34	34	166	166	166	166	236	236
No. of cases	10120	10120	10086	10086	14165	14165	14165	14165	4915	4915	4915	4915	3131	3131
Level	Indiv.	Indiv.	Indiv.	Indiv.	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	HH	HH	HH	HH	HH	HH

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B13: MEA III – nonexperimental decomposition of treatment effects by carded status

	Survey		Leakage								Proportion of HHs doing NREGS work			
	SSP	SSP	NREGS	NREGS	NREGS	NREGS	SSP	SSP	SSP	SSP	NREGS	NREGS	NREGS	NREGS
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
Carded GP			–30	–33			–4.5	–5.0			0.063	0.066		
			(15)	(15)			(4.4)	(4.3)			(0.036)	(0.036)		
p-value			0.044	0.028			0.299	0.247			0.078	0.065		
Have Scard, carded GP	24	24			–71	–75			–12	–12			0.25	0.25
	(7.1)	(7.1)			(23)	(23)			(4.7)	(4.6)			–0.043	(0.042)
p-value	0.001	0.001			0.002	0.002			0.014	0.011			< 0.001	< 0.001
No Scard, carded GP	–2.2	–2.0			3.1	0.2			7.1	6.2			–0.12	–0.11
	(9.9)	(10)			(14)	(14)			(6.2)	(6.2)			(0.044)	(0.044)
p-value	0.820	0.843			0.820	0.988			0.255	0.319			0.008	0.010
Not carded GP	7.7	7.8	–13	–14	–12	–13	–12	–13	–12	–12	0.064	0.066	0.056	0.057
	(9.6)	(9.7)	(21)	(21)	(21)	(21)	(5.8)	(6.1)	(5.8)	(6.1)	(0.044)	(0.044)	(0.047)	(0.046)
p-value	0.426	0.423	0.54	0.501	0.576	0.537	0.036	0.038	0.044	0.045	0.149	0.136	0.231	0.213
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	No	No	No	No	No	No	No	No	No	No	No	No	No	No
BL GP mean	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-values (test of equality):														
Carded GP = not carded GP			0.38	0.35			0.21	0.21			0.98	0.99		
Have SC = no SC	0.017	0.019			< 0.001	0.001			0.0028	0.0043			< 0.001	< 0.001
Adj R-squared	0.0093	0.0095	0.044	0.041	0.052	0.049	0.0085	0.0078	0.013	0.012	0.054	0.053	0.11	0.11
Control mean	236	236	–22	–22	–22	–22	15	15	15	15	0.48	0.48	0.48	0.48
No. of cases	3131	3131	4915	4915	4915	4915	3131	3131	3131	3131	4717	4717	4717	4717
Level	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH

Note: The grey-highlighted rows (p-values) are values we added to the original results.

MEA IV: alternative estimation procedures

Table B14: MEA IV – official and self-reported use of Smartcards

	Official data				Survey data			
	Carded GP		Mean fraction carded payments		Payments generally carded (village mean)		Most recent payment carded (village mean)	
	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: NREGS								
Treatment	0.67	0.67	0.45	0.45	0.38	0.38	0.38	0.38
	(0.045)	(0.089)	(0.041)	(0.110)	(0.043)	(0.108)	(0.042)	(0.101)
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.001	< 0.001	< 0.001
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes
Control mean	0.0046	0.0046	0.0017	0.0017	0.039	0.039	0.013	0.013
No. of cases	880	880	880	880	818	818	818	818
Level	GP	GP	GP	GP	GP	GP	GP	GP
Panel B: SSP								
Treatment	0.79	0.79	0.59	0.59	0.45	0.45	0.45	0.45
	(0.042)	(0.071)	(0.038)	(0.086)	(0.052)	(0.092)	(0.049)	(0.080)
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes
Control mean	0	0	0	0	0.069	0.069	0.044	0.044
No. of cases	880	880	880	880	878	878	878	878
Level	GP	GP	GP	GP	GP	GP	GP	GP

Note: The grey-highlighted rows (p-values) are values we added to the original results; RE – Random Effect; FE – Fixed Effect

Table B15: MEA IV – access to payments

	Time to Collect							
	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	–22	–19	–22	–18	–6.1	–4.6	–3.5	–2.9
	(9.2)	(1.7)	(8.7)	(1.7)	(5.2)	(2.3)	(5.4)	(2.3)
p-value	0.019	< 0.001	0.014	< 0.001	0.244	0.043	0.521	0.200
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes
Week FE	No	No	No	No	No	No	No	No
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes
Control mean	112	112	112	112	77	77	77	77
No. of cases	10191	10191	10120	10120	3789	3789	3574	3574
Level	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.
Survey	NREGS	NREGS	NREGS	NREGS	SSP	SSP	SSP	SSP
	Avg. payment lag (days)				Abs. payment lag deviation (days)			
	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treatment	–5.8	–2.7	–10	–4.7	–2.5	–1.6	–4.7	–2.8
	(3.5)	(4.1)	(3.5)	(0.45)	(0.99)	(0.20)	(1.6)	(0.28)
p-value	0.094	< 0.001	0.005	< 0.001	0.014	< 0.001	0.004	< 0.001
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes
Control mean	34	34	34	34	12	12	12	12
No. of cases	14213	14213	7201	7201	14213	14213	7201	7201
Level	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week
Survey	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B16: MEA IV – official and survey reports of program benefits

	Official				Survey				Leakage			
	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: NREGS												
Treatment	11	8	9.6	6.5	35	22	35	21	–24	–14	–25	–15
	(12)	(9)	(12)	(9)	(16)	(10)	(16)	(10)	(13)	(9)	(13)	(10)
p-value	0.347	0.379	0.425	0.453	0.026	0.030	0.025	0.033	0.067	0.138	0.054	0.123
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Control mean	127	127	127	127	146	146	146	146	–20	–20	–20	–20
N. of cases	5143	5143	5107	5107	5143	5143	5107	5107	5143	5143	5107	5107
Panel B: SSP	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM
Treatment	4.3	8.4	5.1	7.7	12	13	12	11	–7.5	–5.0	7	–4.3
	(5.3)	(5.0)	(5.4)	(5.1)	(5.9)	(5.2)	(6.1)	(5.4)	(3.9)	(3.0)	(3.9)	(3.0)
p-value	0.415	0.093	0.350	0.134	0.045	0.011	0.052	0.034	0.053	0.100	0.079	0.152
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Control mean	251	251	251	251	236	236	236	236	15	15	15	15
No. of cases	3330	3330	3135	3135	3330	3330	3135	3135	3330	3330	3135	3135

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B17: MEA IV – illustrating channels of leakage reduction

	Ghost households (%)				Other over-reporting (%)				Bribe to collect (%)			
	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: NREGS												
Treatment	–0.0095	–0.0095	–0.0091	–0.0091	–0.082	–0.082	–0.084	–0.084	–0.0035	–0.0008	–0.0036	–0.0010
	(0.020)	(0.016)	(0.021)	(0.016)	(0.033)	(0.022)	(0.036)	(0.033)	(0.0085)	(0.0031)	–0.0085	(0.0031)
p-value	0.645	0.561	0.665	0.577	0.014	< 0.001	0.020	0.011	0.678	0.798	0.669	0.749
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Control mean	0.11	0.11	0.11	0.11	0.26	0.26	0.26	0.26	0.021	0.021	0.021	0.021
No. of cases	5278	5278	5242	5242	3953	3953	3672	3672	10375	10375	10304	10304
Level	HH	HH	HH	HH	HH	HH	HH	HH	Indiv.	Indiv.	Indiv.	Indiv.
Panel B: SSP												
Treatment	–2.9	–3.1	–2.4	–2.1	–2.7	–0.6	–3.1	–1.2	–2.3	–1.4	–2.4	–1.4
	(2.7)	(1.7)	(2.7)	(1.7)	(2.9)	(2.5)	(3.0)	(2.5)	(1.9)	(0.75)	(2.0)	(0.80)
p-value	0.278	0.069	0.376	0.205	0.358	0.814	0.293	0.628	0.224	0.056	0.235	0.071
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Control mean	11	11	11	11	1.7	1.7	1.7	1.7	2.5	2.5	2.5	2.5
No. of cases	3330	3330	3135	3135	3165	3165	2986	2986	3165	3165	2986	2986

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B18: MEA IV – access to programs

	Proportion of HHs doing NREGS work				Was any HH member unable to get NREGS work in				Is NREGS work available when anyone wants it?	
	Study period	Study period	Study period	Study period	May	May	January	January	All months	All months
	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	0.072	0.072	0.071	0.071	–0.023	–0.023	–0.027	–0.027	0.027	0.027
	(0.033)	(0.029)	(0.033	(0.031)	(0.027)	(0.027)	(0.033)	(0.037)	(0.015)	(0.010)
p-value	0.03	0.012	0.034	0.021	0.398	0.395	0.41	0.465	0.079	0.005
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
BL GP mean	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Control mean	0.42	0.42	0.42	0.42	0.20	0.20	0.42	0.42	0.035	0.035
No. of cases	4943	4943	4909	4909	4748	4748	4496	4496	4755	4755
Level	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH

	Is NREGS work available when anyone wants it?		Did you have to pay anything to get this NREGS work?				Did you have to pay anything to start receiving this pension?			
	All months	All months	NREGS	NREGS	NREGS	NREGS	SSP	SSP	SSP	SSP
	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM	OLS FE	GLMM
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Treatment	0.024	0.024	–0.0003	0.0018	–0.00054	0.0015	–0.046	–0.046	–0.055	–0.055
	(0.015)	(0.011)	(0.0015)	(0.0017)	(0.0015)	(0.0017)	(0.031)	(0.032)	(0.039)	(0.042)
p-value	0.119	0.024	0.840	0.295	0.719	0.395	0.137	0.146	0.159	0.189
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District RE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
BL GP mean	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Control mean	0.035	0.035	0.0022	0.0022	0.0022	0.0022	0.075	0.075	0.075	0.075
No. of cases	4715	4715	7185	7185	6861	6861	581	581	352	352
Level	HH	HH	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.	Indiv.

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B19: MEA IV – nonexperimental decomposition of treatment effects by carded status

	Time to collect				Payment lag				Survey					
	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	SSP	SSP
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Carded GP	–33	–29			–5	–4			37	18			14	11
	(8.1)	(1.8)			(2.8)	(0.3)			(17)	(11)			(6.2)	(5.8)
p-value	< 0.001	< 0.001			0.081	< 0.001			0.030	0.106			0.025	0.055
Have Scard, carded GP			–33	–29			–4.4	–3.1			152	84		
			(8.4)	(2.2)			(3)	(0.4)			(24)	(13)		
p-value			< 0.001	< 0.001			0.146	< 0.001			< 0.001	< 0.001		
No Scard, carded GP			–33	–30			–5.9	–4.4			–55	–61		
			(8.6)	(2.1)			(2.8)	(0.4)			(17)	(13)		
p-value			< 0.001	< 0.001			0.04	< 0.001			0.001	< 0.001		
Not carded GP	4.9	5.0	4.9	4.9	–7.4	–0.9	–7.5	–1.0	22	20	19	14	8.3	12.3
	(13)	(2.2)	(13)	(2.2)	(5)	(0.4)	(5)	(0.4)	(26)	(14)	(26)	(13)	(9.6)	(7)
p-value	0.704	0.023	0.708	0.026	0.136	0.028	0.131	0.016	0.385	0.131	0.454	0.284	0.386	0.080
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No	No	No
District RE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
BL GP mean	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
p-values (test of equality):														
Carded GP = not carded GP	< 0.001	< 0.001			0.45	< 0.001			0.50	0.84			0.54	0.86
Have SC = no SC			0.88	0.88			0.37	0.002			< 0.001	< 0.001		
Control mean	112	112	112	112	34	34	34	34	166	166	166	166	236	236
No. of cases	10120	10120	10086	10086	14165	14165	14165	14165	4915	4915	4915	4915	3131	3131
Level	Indiv.	Indiv.	Indiv.	Indiv.	Indiv-Week	Indiv-Week	Indiv-Week	Indiv-Week	HH	HH	HH	HH	HH	HH

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Table B20: MEA IV – nonexperimental decomposition of treatment effects by carded status

	Survey		Leakage								Proportion of HHs doing NREGS work			
	SSP	SSP	NREGS	NREGS	NREGS	NREGS	SSP	SSP	SSP	SSP	NREGS	NREGS	NREGS	NREGS
	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC	With PC	No PC
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
Carded GP			–30	–19			–4.5	–2.0			0.063	0.085		
			(15)	(11)			(4.4)	(3.2)			(0.036)	(0.016)		
p-value			0.044	0.070			0.299	0.531			0.078	< 0.001		
Have Scard, Carded GP	24	22			–71	–47			–12	–7			0.25	0.17
	(7.1)	(6.4)			(23)	(12)			(4.7)	(3.6)			–0.043	(0.018)
p-value	0.001	< 0.001			0.002	< 0.001			0.014	0.044			< 0.001	< 0.001
No Scard, carded GP	–2.2	–6.3			3.1	14			7.1	6.7			–0.12	–0.024
	(9.9)	(7.4)			(14)	(13)			(6.2)	(4.1)			(0.044)	(0.020)
p-value	0.820	0.398			0.820	0.296			0.255	0.104			0.008	0.216
Not carded GP	7.7	11.7	–13	–5	–12	–2	–12	–9	–12	–9.2	0.064	0.078	0.056	0.070
	(9.6)	(7.0)	(21)	(13)	(21)	(13)	(5.8)	(3.9)	(5.8)	(3.9)	(0.044)	(0.019)	(0.047)	(0.019)
p-value	0.426	0.094	0.54	0.726	0.576	0.879	0.036	0.028	0.044	0.017	0.149	< 0.001	0.231	< 0.001
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	No	No	No	No	No	No	No	No	No	No	No	No	No	No
District RE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
BL GP mean	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-values (test of equality):														
Carded GP = not carded GP			0.38	0.23			0.21	0.08			0.98	0.70		
Have SC = no SC	0.017	< 0.001			< 0.001	< 0.001			0.0028	< 0.001			< 0.001	< 0.001
Control mean	236	236	–22	–22	–22	–22	15	15	15	15	0.48	0.48	0.48	0.48
No. of cases	3131	3131	4915	4915	4915	4915	3131	3131	3131	3131	4717	4717	4717	4717
Level	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH

Note: The grey-highlighted rows (p-values) are values we added to the original results.

Appendix C: Theory of change analysis

Can we identify moderating factors that contribute to the heterogeneous effects?

Table C1: Theory of change analysis – official and self-reported use of Smartcards

Test of treatment heterogeneity	Official data				Survey data			
	Carded GP		Mean fraction carded payments		Payments generally carded (village mean)		Most recent payment carded (village mean)	
	NREGS	SSP	NREGS	SSP	NREGS	SSP	NREGS	SSP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
F-Stat	5.06	4.15	6.31	35.39	1.72	2.23	2.28	1.04
p-value	0.0259	0.0434	0.0130	< 0.001	0.1915	0.1378	0.1330	0.3083
No. of cases	880	880	880	880	818	878	818	878

Table C2: Theory of change analysis – access to payments

Test of treatment heterogeneity	Time to collect				Avg. payment lag (days)		Abs. payment lag deviation (days)	
	NREGS	NREGS	SSP	SSP	NREGS	NREGS	NREGS	NREGS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
F-Stat	3.03	1.76	1.67	3.26	0.68	0.01	0.03	0.71
p-value	0.0837	0.1865	0.1986	0.0728	0.4124	0.9157	0.8519	0.4022
No. of cases	10191	10120	3789	3574	14213	7201	14213	7201

Table C3: Theory of change analysis – official and survey reports of program benefits

Test of treatment heterogeneity	Official		Survey		Leakage	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: NREGS			
F-Stat	0.97	1.02	1.03	1.33	0.03	0.05
p-value	0.3257	0.3133	0.3120	0.2508	0.8595	0.8166
N. of cases	5143	5107	5143	5107	5143	5107
			Panel B: SSP			
F-Stat	0.41	0.63	0.00	0.01	1.00	1.08
p-value	0.5222	0.4280	0.9976	0.9429	0.3189	0.3013
No. of cases	3330	3135	3330	3135	3330	3135

Table C4: Theory of change analysis – illustrating channels of leakage reduction

Test of treatment heterogeneity	Ghost households (%)		Other over-reporting (%)		Bribe to collect (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: NREGS			
F-Stat	0.02	0.02	1.78	3.69	4.86	5.39
p-value	0.8803	0.8927	0.1840	0.0564	0.0290	0.0216
N. of cases	5278	5242	3953	3672	10375	10304
			Panel B: SSP			
F-Stat	0.18	0.30	0.11	0.14	1.51	1.47
p-value	0.6756	0.5846	0.7462	0.7061	0.2211	0.2274
No. of cases	3330	3135	3165	2986	3165	2986

Table C5: Theory of change analysis – access to programs

Test of treatment heterogeneity	Proportion of HHs doing NREGS work		Was any HH member unable to get NREGS work in		Is NREGS work available when anyone wants it?		Did you have to pay anything to get this NREGS work?		Did you have to pay anything to start receiving this pension?	
	Study period	Study period	May	January	All months	All months	NREGS	NREGS	SSP	SSP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
F-Stat	0.02	0.02	1.08	2.65	0.45	0.36	0.10	0.33	1.34	1.15
p-value	0.8945	0.8811	0.3004	0.1057	0.5051	0.5506	0.7574	0.5643	0.2481	0.2848
No. of cases	4943	4909	4748	4496	4755	4715	7185	6861	581	352

Table C6: Theory of change analysis – nonexperimental decomposition of treatment effects by carded status

Test of treatment heterogeneity	Time to collect		Payment lag		Survey		
	NREGS	NREGS	NREGS	NREGS	NREGS	NREGS	SSP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
F-Stat	1.12	1.11	0.67	0.64	1.48	2.35	0.04
p-value	0.2921	0.2928	0.4153	0.4254	0.2261	0.1271	0.8477
No. of cases	10120	10086	14165	14165	4915	4915	3131

Test of treatment heterogeneity	Survey	Leakage				Proportion of HHs doing NREGS work	
	SSP	NREGS	NREGS	SSP	SSP	NREGS	NREGS
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
F-Stat	0.01	0.03	0.13	0.81	0.58	0.13	0.61
p-value	0.9265	0.8636	0.7181	0.3695	0.4458	0.7181	0.4347
No. of cases	3131	4915	4915	3131	3131	4717	4717

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