Can Health Workers Automate Their Way to Better Monitoring - Experimental Evidence from Tuberculosis Control in India

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THIS DRAFT: June 2016

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Abstract

In its most common form, tuberculosis (TB) is a curable disease that still kills around 300,000 people every year in India. Combating the disease requires improving case finding and ensuring treatment adherence. This paper exploits the random placement of biometric devices recording TB patients' adherence to treatment and health workers' attendance at treatment centers in urban slums across four Indian states. First, we find that patients seeking treatment in a treatment center equipped with a biometric monitoring device are 20% less likely to interrupt their treatment than those enrolled in a regular center. This is driven by an improved attendance of both patients and health workers at the treatment center and by an improved health worker productivity. Second, the use of biometric devices significantly reduces misreporting of performance by health workers. Biometric monitoring appears as a promising tool for re-enforcing TB control strategies.

Introduction

With 1.8 million deaths annually, Tuberculosis (henceforth TB) is the most lethal infectious disease globally. India has by far the largest number of cases, with 23 percent of the global total and more than the next two most affected countries combined (WHO, 2015). Drug-resistant TB poses specific epidemiological threats and requires innovative treatment technologies, but 97 percent of new TB cases are caused by drug-susceptible strains of the disease, which can be cured by a mix of ubiquitous first-line antibiotics. With the large adoption of the DOTS system (Directly Observed Therapy), Governments commit to making these drugs available for free to all patients through their National TB Control Programs. However, public programs for TB control still face two main challenges: patients need to be diagnosed and enrolled in the treatment, and they must adhere to the full course of the treatment. Health systems have strived to improve the quality of service delivery to address those challenges, but the staggering number of TB-related deaths calls for further progress. The increasing availability of information and communication technology (ICT) in developing countries has raised hopes for improved service delivery of public programs. While complex interventions ensuring that patients adhere to prescribed medication have been studied extensively in OECD countries (Bhatnagar et al. 2012), there is no rigorous evidence on innovative strategies improving adherence to TB medications in developing countries[1].

This paper examines the benefits of leveraging two technological advances for TB control in India: connectivity that enables closer monitoring of service delivery in remote areas and biometric identification that enables the creation of reliable registers of assistance beneficiaries.

The rapid progress in internet connectivity and mobile phone coverage in developing countries has created unprecedented opportunities for enhanced monitoring of program performances and improved reactivity to the needs of beneficiaries. In the health sector, mobile technology has been used to send text message reminders to patients, which helped boost adherence to anti-malarial treatment in Northern Ghana (Raifman et al., 2014) and antiretroviral treatment in Kenya (Lester et al., 2010; Pop-Eleches et al., 2011). Mobile communication can also be targeted to health workers, as was the case in Ethiopia with automated messages to remind health workers of key appointments with pregnant women and newborns and help track the stock of essential medicines (Otto et al, 2015), or in Kenya with messages

[1] See Bhatnagar et al. 2012 for a review of the factors that prevent adherence to tuberculosis treatment regimens.

to improve health worker's adherence to guidelines for malaria treatment (Zurovac et al., 2011). The intervention evaluated in this paper is also targeted to health workers.

Biometric identification has seen a rapid growth in the past decade and has now been used as a mechanism for delivering public programs in more than 80 developing countries, with applications ranging from financial services to social transfers, civil service reforms or health policies (Gelb and Clark, 2013). Evidence on the impact of biometric identification for beneficiaries is encouraging but still scarce. Studies have shown biometric technology to increase the efficiency of payments in cash-for-work and pension programs (Muralidharan et al, 2014) and fuel subsidies (Barnwal, 2015) in India, and improve credit repayment rates in Malawi (Gine et al, 2012).

We partnered with Operation ASHA, the largest NGO delivering primary care to TB patients in India, to randomize the roll-out of biometric devices across 130 treatment centers, each covering a population of about 22,500 individuals, located in urban slums across four states in Northern India: Madhya Pradesh, Delhi, Chhattisgarh and Odisha. The biometric devices were used to perform three main functions: identifying new patients and enrolling them in the record system with minimal room for errors in reporting; accelerating follow-up by health workers by generating alerts when patients fail to take their pills; creating a real-time tool for program managers to monitor attendance and performance of health workers.

We find that biometric monitoring reduces patients' interruption of their TB treatment before its completion by 2.3 percentage points (24 percent). This impact is large and important, given the large risks and externalities associated with treatment interruptions. It is driven by a higher patient and health worker attendance at the treatment centers, higher levels of efforts dedicated by service providers to following up with patients who miss a pill, and higher efficiency in doing so.

In addition to the reduction of treatment interruption, biometric monitoring improves the quality of data reporting. It significantly reduces the over-reporting of patient detection as well as the under-reporting of treatment interruption both in DOTS centers and in government registers, suggesting some collusion between NGO and government TB health workers in data misreporting.

The analysis links the previously parallel literatures on public health delivery and digital technology. Bhatnagar et al. (2012) use open-ended questions to elicit the perceived impact of biometric monitoring on patients' visits and health workers' presence at the DOTS center. This study innovates in using a randomized design to solve selection issues and rigorously quantify the impact of the technology. Our results are in line in showing an increase in patient and health worker attendance but differ in that we find no evidence of an improved patient-health worker relationship. We also add to that study by investigating two novel outcomes: treatment interruption and quality of reporting.

The remainder of the paper is organized as follows. Section 1 provides background on Tuberculosis in India and on biometric monitoring in DOTS centers. Section 2 describes the experimental setup and the data. Section 3 presents samples and balance checks. Sections 4 and 5 describe the estimation strategy. Quantitative results are presented in Section 5, qualitative results in Section 6. Section 7 concludes.

1- Background

1.1 TB control in India

TB remains the largest infectious killer of adults, claiming nearly 1.8 million lives annually, of which about 350,000 are in India. In other words, fully 1000 people die of TB every day in India, even though effective first-line antibiotics are available for free all over the country to treat drug-susceptible strains of the disease, which account for roughly 97 percent of all new TB cases (WHO, 2015). Two major challenges hinder faster progress in the fight against TB and call for strong public health programs: detecting infected patients and enrolling them in treatment in a timely manner and ensuring that they complete the full course of treatment. The first challenge, known as early case finding, is critical to improve the condition of the infected patient, but also to prevent the spread of the air-borne, highly contagious disease. In settings where people have very little access to and information on care and preventive services, early diagnosis and enrollment in the treatment may require dedicated interventions on the part of public health systems. The second challenge, treatment compliance, is of primary importance for preventing the development and transmission of drug-resistant strains of the disease. Yet it is particularly complex. In order to be cured, an infected patient needs to take a cocktail of up to 7 drugs at a time on a strict schedule: three days per week continuously over a 6- to 8-month period. Following only a few months of the treatment, usually as early as two months, the symptoms of tuberculosis tend to wane off -- but the side effects of the drugs remain. This leads patients to discontinue treatment early in the absence of a strong health care support system to ensure their compliance with the full prescribed treatment course.

In response to the dual challenge of increasing detection and ensuring compliance, India and other countries have adopted the delivery model program known as Directly Observed Therapy, Short Course (DOTS). In the DOTS model, medications are kept in locally established care centers and patients ingest each dose under direct observation by the medication providers. Bringing health care services closer to communities, including smear microscopy technology for diagnosis, aims at boosting detection of new TB patients. Direct observation by a trained provider, and the maintenance of individual treatment cards recording pill intake, aim at improving follow-up by health workers in case of non-compliance.

While the implementation of DOTS has improved the response to TB, the system still suffers from certain shortcomings, some of which are linked to the paper-based format of the record system. A first shortcoming is the inaccuracy of reporting of new cases. Human error and omissions can lead to missing patients, or may leave room for health workers to over- or under-report numbers of patients enrolled. A second shortcoming of the paper-based record system is its inadequacy for real-time follow-up in case of missed pills. Primary providers are in charge of monitoring pill intake and following up as needed, but they have little incentive to commit time and efforts to this additional work in the absence of rigorous monitoring. Treatment records are collected by the TB control program only once every one to two months. By that time, it may be too late and in any case very difficult to bring back the patients who missed a pill into the regular course of the treatment.

To help address those challenges, in 2012 the Government of India launched a web-based centralized database of all TB patients called *Nikshay*. By digitizing the paper-based treatment cards, *Nikshay* is meant to keep track of test results, prescribed medication, days when patient took the medicine and missed a dose. About 7,000 health workers were hired to visit centers and digitize treatment cards, and access to the database was given to TB officers, contractual employees, large hospitals and nonprofits so they could update the records. By aggregating TB records from across India in one unique dataset, *Nikshay* serves as a dashboard for the National TB Control Program. Yet as it relies on the digitization of paper-based documents, *Nikshay* is not set up for identifying duplicates or establishing unique identity. The quality of the database is entirely reliant on the quality of information on the paper-based treatment cards. The digitization process may even add a layer of potential error in the recording system. Further, the digitization process is implemented with a lag of about one to two months between when the patient misses a dose and when the corresponding information gets entered in the electronic database, thus disabling any quick corrective action to ensure patient compliance.

Biometric identification technology is increasingly available in India, in particular since the national roll-out of *Aadhaar*, an ambitious program that aims to provide a biometrics-based Unique Identification (UID) to all the 1.2 billion residents. *Aadhaar* is a 12 digit individual identification number issued by the Unique Identification Authority of India on behalf of the Government of India, which serves as a proof of identity and address, anywhere in India. The identity of any individual who has an *Aadhaar* ID can be authenticated through fingerprint scan, iris scan and registered cellphone number. Currently *Aadhaar* covers about 850 million individuals, corresponding to about 70% penetration among the adult population. The objective of the Government of India is to expand the system enough for various social programs to use it as a platform for service delivery.

With *Nikshay* and *Aadhaar*, the infrastructure is therefore in place for using a biometric recognition technology linked in real time to an integrated database of care beneficiaries, which would massively improve the reliability of records and enable rapid follow-up on patients who miss pills. In such an integrated system, the *Aadhaar* ID could be used at the time of registering patients into *Nikshay*, and each visit could be recorded automatically into the database using *Aadhaar* authentication. The system studied in this paper can therefore be seen as a pilot for a national system based on the integration of two existing technologies.

1.2 Operation ASHA and the eCompliance system

Operation ASHA (henceforth OA) is an NGO based in New Delhi, and one of the leading non-profit TB DOTS providers in India. Since its creation in 2006, OA has operated 194 centers and treated about 9,000 patients. The treatment centers are located in 16 cities and 2 tribal blocks spread across 8 states. OA hires health workers to operate 2 centers each. Health workers deliver information to the community, engage in the detection of new patients through widespread community testing, and track patients enrolled in the center who have missed a pill to bring them back onto the regular course of treatment. They are supposed to receive a base salary as well as detection-based incentives of Rs. 150

per detection. However, there is some uncertainty around health workers' expectations on the nature of their salary as well as on their perceptions of their actual salary. 55% of counselors at baseline report not receiving any incentives. While at midline 70% report to have received incentives, at endline only 32% report to have received incentives. The reporting does not vary significantly across treatment and control.

Since 2011, and in partnership with Microsoft Research India, OA has developed and used eCompliance, an electronic, biometric tool to ensure that health workers can accurately follow-up with all their TB patients. This tool combines a software system on a simple notebook computer with a fingerprint scanner, all for a cost of less than U.S. $250 per treatment center.

eCompliance first uses the health worker's fingerprints to record her daily arrival and departure time from the center. In addition, whenever a new patient starts taking medicine at the center, her fingerprints are registered and her profile created in the system. Her fingerprints are then taken again each time she comes to the center to take her medicine during the entire course of the treatment. In addition to the terminal installed in the treatment center, the health worker can use a portable terminal to record the administration of pills at patients' home. The system thus automatically keeps track of all pill intakes in a simple compliance log. Its user-friendly interface allows health workers to easily view each patient's pill intake history and to access the list of patients that have missed a daily dose and require a specific action on the health workers' part.[2]

The data is stored in two different places: in the terminal located in the health center, and in a server located in New Delhi. Daily communication between the local terminals and the central server ensure that no data gets lost. In addition, it facilitates the monitoring of local health workers by the senior hierarchy of the organization.[3]

2- Experimental setup and data sources

[2] The system further keeps track of patients' lab sputum test results, and automatically reminds the health worker when a new test is due. It also calculates the health workers' salaries and communicates it to the finance department of the NGO.
[3] In the centers, the fingerprint scanner is connected to the computer through a USB interface. The computer has a SIM card with a 2G internet data plan through which it sends and receives information to the central server. The terminals can also interact with the server by sending SMS texts. Although this latter option is more expensive, it is useful in areas where 2G connection is unreliable.

2.1 Experimental setup

The experiment was conducted in Northern India, spread across nine cities in four states, Madhya Pradesh, Delhi, Chhattisgarh and Odisha. Each Operation ASHA health worker operates two DOTS centers, usually in their own community or close to the area where they live. The randomization was done at the health worker level and stratified at the city level, such that each pair of centers operated by a health worker was randomly assigned to the treatment group receiving biometric devices or to the control group. The installation of biometric devices was phased in across cities between mid-March and mid-September 2013. The study duration spanned an average of 13 months in each city. Other than installing the biometric devices, the intervention consisted of a two-hour training for health workers on how to use the device and of registering and enrolling current patients on the server. The DOTS centers are located in non-overlapping and scattered areas and health workers are permanently assigned to their catchment areas, limiting the scope for interactions between health workers of different treatment groups and for other spill-over effects.

2.2 Data sources

Data were collected from four main sources: quantitative surveys administered to patients and health workers, program and administrative data from OA and government registers, independent random visits, and qualitative interviews with patients and health workers.

Survey data

To assess the impact of the program on treatment adherence, we rely on data from quantitative surveys collected throughout the course of the experiment with 3409 **patients**. In 35% of cases, patients were surveyed twice: once at the onset of their treatment (entry), once after they completed their treatment (exit). Sampling was conducted a monthly basis during center visits and consisted in identifying all patients starting their treatment as well as all patients who had completed six months of treatment or had interrupted their treatment. The extensive patient questionnaire collects a large amount of information on socio-demographic characteristics, location, health symptoms, TB history and knowledge, interactions with health care providers, employment and financial situation, consumption and well-being. Additional modules investigated the drivers of treatment interruption when appropriate.

Most patients were interviewed at home. Three attempts were made to locate the patient before they were declared “Not found”.

Health worker surveys were typically administered three times: (i) right before the installation of the biometric devices (baseline), (ii) after about 6 months of intervention (midline), (iii) at the end of the intervention 6 to 8 months after midline (endline). The questionnaires allow for detailed information on the health workers’ socio-economic background, employment history, motivation and satisfaction, interactions with patients and with OA. For health workers who quit OA during the intervention, an additional module investigated the motivations for employment termination.

Program and administrative data

Salary sheets and productivity reports were collected monthly from Operation ASHA. Productivity reports are produced by health workers and contain data on the number of new patients enrolled and new cases of non-compliance for each center per month, in addition to the data on monthly outcomes such as cases of patient transfer, patient death, and treatment failure.

TB registers and lab registers are kept by public health TB officers, who centralize the treatment cards generated by all centers in the area, whether operated by OA or not. These registers list the name and address of all enrolled patients, the dates and results of their initial and follow-up sputum tests and the outcome of the treatment.

Treatment cards are maintained by Operation ASHA health workers. Each newly enrolled patient is assigned a treatment card that contains detailed information about daily treatment adherence, type of TB and sputum test results.

Random visits

Independent random visits were conducted by the survey staff to OA centers or mobile areas to collect data on health worker and patient attendance, health workers’ activities at the center and during home visits, collect data from patient treatment cards as well data related to the usage of biometric devices. Each center received an average of 2 random visits per month. On visit days, the research team would stay at the center (or accompany the health worker if the health worker was a mobile worker) from the time it opened in the morning till the health worker finished his work, around early afternoon.

Qualitative interviews

To better explore mechanisms and inform the discussion of our results, we conducted semi-structured qualitative interviews with a subset of 47 patients and 45 health workers across 7 cities at the end of experiment. Open-ended questions related to (i) health workers' intrinsic motivation, (ii) effort reallocation or (iii) multitasking and data reporting. Interviews were conducted in Hindi, paying special attention to aspects such as question order (non-threatening to risky), nature of questions ("grand-tour" questions, structured questions, hypothetical interaction questions), and inclusion of numerous prompts to probe into open-ended questions.

3- Sample Description and Balance Checks

3.1 Health workers

Our initial sample was composed of 66 health workers, operating Operation ASHA centers in Madhya Pradesh, Delhi, Chhattisgarh and Odisha. More than a third of the initial sample of health workers dropped out over the course of the experiment, and all but three were replaced. Our final sample thus comprises a total of 87 health workers, 42 in the treatment group, 45 in the control group, operating 130 DOTS centers. Figure 1 shows the geographical distribution of health workers in our sample. 50 are located across four cities Madhya Pradesh, 21 in three cities in Chhattisgarh, 6 in Delhi, 10 in Odisha. The study spanned between March 2013 and September 2014, with different start dates across States. Each health worker stayed for an average duration of 10 months in the experiment.

Because differential attrition could introduce a selection bias, we analyze health workers' attrition in Table A1 and A2 in Appendix. As reported in Table A1, the likelihood of a health worker dropping out is not significantly affected by the random assignment of biometric devices to centers. Results show that dropouts occurred more often in Sagar and Delhi, and among men and health workers without prior work experience. Health workers' attrition is not significantly affected by any other socio-demographic characteristics, exposure to technology, performance or motivation at baseline, limiting the risk for our impact estimates to be biased by a relatively high turn-over. Table A2 shows that the initial sample and the final sample only differ significantly by two characteristics out of twenty tested, which is not more than would be expected.

Table 1 presents summary statistics for the community health workers. We present means for the full sample and by treatment groups, as well as p-values for tests comparing means across treatment groups. Health workers are 31 years old on average. Most (74 percent) of them are men, 41 percent belong to the general caste and 81 percent are Hindus. Health workers are well-educated on average with a majority of them completing secondary education or higher. 14 percent have a university degree and only 4 percent did not complete class 10. While 74 percent of the health workers had previous work experience, for an average of 9 years, only 15 percent worked the social/NGO sector. A majority (55 percent) of health workers live in a neighborhood where one of the centers that they operate is located. They mostly live in decent conditions: almost all of them have electricity at their place and two thirds have access to tap water. More than half of them own some land. In terms of exposure to technology, 57 percent know how to use a computer and 41 percent have an email account.

3.2 Patients

A total of 3415 patients were surveyed at least once over the course of the experiment. We provide a statistical description of the socio-demographic characteristics for the full set of patients as well as for baseline patients, who were detected and enrolled in DOTS centers before the onset of the experiment in Table 2. Patients are 34 years old on average. Men and women are almost equally represented, although there is a slight majority of men (57 percent). They belong to the most deprived castes in India: the Scheduled Castes and Scheduled Tribes, or Dalits (33 percent) and Other Backward Classes (36 percent). Only 18 percent belong to the better-off General category, which does not receive any government benefit. By comparison, 41 percent of health workers reported belonging to a caste classified under the General category. Patients are 86 percent Hindu. They are relatively literate. Only 30 percent of them cannot read or write and only 22 percent have no schooling at all. Half of them have always lived in the same place.

Panels B and C of Table 2 report summary statistics on the patient's previous exposure to TB and their medical history respectively. A large majority (71 percent) report being vaccinated against Bacillus Calmette–Guérin (BCG), and the surveyor could verify the vaccination mark in 80 percent of the cases. TB patients have high exposure to TB on average. A quarter of them report having past occurrences of TB, and 41 percent of the patients interviewed belong to a household where at least one member had TB since they were born. Among those who consulted a medical facility over the previous three months, almost half consulted with a private doctor, 40 percent received an injection and they spent an average of Rs. 1220 for the first visit.

The last column in table 2 reports the *p-value* of the test that the difference between means in the control group and in the treatment group is null. For this baseline balancing test, we restrict the sample to the subset of patients currently enrolled in the DOTS centers at the onset of the experiment. Patients in both groups appear to have very similar socio-demographic characteristics at baseline. There is some imbalance along the health dimension (Panels B and C). Patients in the treatment group have had TB a higher number of times and their family members are significantly more likely to have had TB. They are also more likely to have consulted a private doctor when ill as opposed to a government doctor. In the results presented below, we check the robustness of our estimates to controlling for variables that are significantly different between the two groups as controls.

4- Estimation strategy

We estimate the average impact of monitoring TB treatment adherence and health workers' attendance in DOTS centers on a series of patient outcomes, from the survey data, by running the following regression:

$$Y_i = \alpha_1 + \beta_1 T_i + X_1' \gamma_1 + \delta_1 Y_{0i} + \sum_c \theta_{1c}^i + \varepsilon_{1i} \quad (1)$$

where Y_i is the treatment adherence indicator for patient i, T_i is a dummy equal to 1 if the patient was allocated to a health worker in the treatment group and 0 otherwise, X_1' is a vector of patient controls including age, gender, religion, household size, whether the patient had TB in the past and binary variables for the type of survey administered. Y_{0i} is the outcome measured at baseline, and θ_{1c}^i are city fixed effects (the level of stratification). The key coefficient of interest is β_1, which estimates the difference in treatment adherence outcome induced by biometric monitoring. In this and all other regressions, we adjust standard errors for clustering at the health worker level since the randomization was conducted at this level.

We next evaluate the average effect of biometric monitoring devices on a series of indicators measured at the center level through random visits, including patient and health worker attendance at the DOTS center as well as health worker effort and productivity, by using the following specification:

$$Y_i = \alpha_2 + \beta_2 T_i + X_2' \gamma_2 + \sum_c \theta_{2c}^i + \varepsilon_{2i} \quad (2)$$

where Y_i is the outcome measured during visit i, T_i is a dummy equal to 1 if the visit was made to a center under biometric monitoring and 0 otherwise, X_2' is a vector of health worker controls including health worker's age, and binary variables indicating the health worker's education level, whether the health worker belonged to "General caste" category, and whether the health worker was Hindu. θ_{2c}^{i} are city fixed effects.

We are also interested in estimating the impact of biometric monitoring on outcomes measured at the health-worker level such as effort and productivity, for which we run regressions of the following form:

$$Y_i = \alpha_3 + \beta_3 T_i + X_3' \gamma_1 + \delta_3 Y_{0i} + \sum_c \theta_{3c}^{i} + \varepsilon_{3i} \qquad (3)$$

where Y_i is the outcome measured for health worker i, T_i is a dummy equal to 1 if the health worker operated a center equipped with biometric monitoring and 0 otherwise, X_3' is a vector of health worker controls including health worker's age, and binary variables indicating the health worker's education level, whether the health worker belonged to "General caste" category, and whether the health worker was Hindu. Y_{0i} is the outcome measured at baseline, and θ_{3c}^{i} are city fixed effects

We finally turn to estimating how the use of digital technology in the DOTS centers affects the quality of productivity reporting by health workers, using productivity report data. For this, we use the specification of equation (3) but the unit of observation is a monthly report for a given health worker.

For all equations, coefficients are estimated using ordinary least square (OLS) regressions.

5- Results

5.1 Impact on treatment adherence

Table 3 reports estimates of impact on patient behavior. Treatment adherence significantly improves with the use of biometric equipment in DOTS centers (Panel A). Patients attending centers equipped with the device are 2.3 percentage points less likely to interrupt their treatment before its completion, a 24 percent increase to the 9.7 percent likelihood of interrupting the treatment for patients in control centers (col. 1). This difference is statistically significant at the 5 percent level. Results on intermediary outcomes measuring compliance to TB treatment obtained from treatment cards show a similar trend. Patients under biometric monitoring are 62.9 percent less likely to miss their pills on a day when they are supposed to take some (Col. 2) and they have an additional 36.7 percent chance to miss their pills at least once during the course of their treatment as compared to patients under regular monitoring (Col. 3).

Improvement in treatment adherence is likely driven by:

(i) an increased patient attendance at the center

Random visit data were collected during a day-long monitoring visit to each center on a four-weekly average frequency. On a visit day, 27 percent more patients are likely to visit the center to take their treatment in a biometrics center (Panel B, col. 1), despite no significant difference between treatment and control groups in the average number of patients per center at baseline. In addition, the share of scheduled patients who actually visited the center on the day they were supposed to is 30 percent higher in centers equipped with biometric devices (col. 2). Further, patients in the treatment group are 20 percentage points less likely to report occasionally sending someone else to pick up the pills on their behalf at the DOTS center, significant at the 1 percent level (col. 3 and 4). They also are 7 percentage points less likely to collect a set of pills for a duration of one week or more in one single visit, also significant at the 1 percent level (col. 5 and 6). These results show that the biometric devices reinforced the DOTS model by making it more likely that patients come and take their treatment in the health center rather than taking pills home for self-administration, which in turn translates into improved adherence to treatment. The impact appears to be stronger for relapsing patients, who have the highest risk of developing multi-drug resistance (significant at 10 percent, not shown here).

(ii) an increased health worker attendance at the center

Results on treatment compliance may also be driven by an improved service delivery. Results in Table 4, Panel A show the significantly positive impact of biometric devices on health workers' attendance, both at the extensive and intensive margin. In the control group, the probability that the health worker is present at the DOTS center during a random spot check is only 2.2 percent. This probability reaches 13.9 percent in biometrics centers (Col. 1). Health workers operating centers with biometric monitoring also work longer hours: the installation of a biometric device in the DOTS center increases the health worker's presence at the center of 31 minutes per shift (half-day), a 25 percent increase compared to the 2 hours presence per shift in control centers (Col. 2). Biometric monitoring not only increases health worker's attendance but also that of their supervisors (col. 3 and 4), who are 3.7 percentage points more likely to be present at the center on a day-long monitoring visit than those in regular centers.

(iii) an increased health worker effort and productivity

Biometric devices not only increase attendance but also effort. Home visits to patients who cannot visit the treatment center increase significantly, both intensively and extensively (Panel B, col. 1 and 2).

Biometric monitoring also raises productivity at the same level of effort. Health workers who use biometric devices report facing significantly fewer challenges to get patients to complete treatment (col 3 and 4). The technology involved is not only a tool for monitoring patients and health workers, it also improves workers' productivity by providing on-time information on patient adherence to treatment, thereby making facilitating one of their main tasks.

However, the quality of the health worker - patient interaction does not seem to be affected by the technology. Patients do not report receiving more information from their counselors or seeing any increase in the interaction with them (Panel C).

5.2 Impact on quality of reporting

(i) Quality of reporting on treatment adherence

Table 5 shows estimates of the average effect of biometric monitoring on the quality of reporting by health workers on treatment adherence. While the program significantly reduces the likelihood of interrupting the TB treatment, there is no significant impact on treatment adherence, as recorded by health workers in their monthly reports (Panel A col 1 and 2). This could be due to biometric monitoring making it more difficult for health workers to underreport treatment interruption. The actual reduction in treatment interruption could be offset by a more truthful reporting in treatment centers. We further explore the possibility that biometric monitoring reduces the scope for misreporting on TB treatment compliance by looking at the impact of biometrics on pill delivery as was independently observed during the research team monitors' random visits. The probability that pills are delivered during that visit is 10 percent higher in biometrics centers than in regular DOTS centers (col. 3) most likely because patients reportedly took their pills earlier (col. 4) or because they take them from another facility (col. 5) which suggests that biometric monitoring might also affect misreporting over patients enrolled in a center. Results in Table A4 in appendix show that government registers report no significant difference in treatment outcome either between patients treated in biometric centers and those treated in regular centers, suggesting that there might be collusion between NGO health workers and government officers. We provide qualitative evidence for this statement in section 6 below.

(ii) Quality of reporting on patient detection

In Table 6, we investigate whether biometric monitoring might improve the quality of reporting on patients newly enrolled in DOTS centers. Program data show that the number of new patients *reportedly* detected every month by health workers operating centers equipped with digital technology is significantly lower than that in control centers, a 33% reduction (Panel A col 1 and 2). This contrasts with the absence of significant impact on the number of independently verified detections (col 3 to 5). Verified detections account for patients whom were successfully surveyed at the onset of their treatment (entry) among new patients reportedly detected. Verified patients in control centers were twice as likely to never have met the OA health worker than those in treatment centers (col. 6), while this impact is not significant for patients detected before the onset of the experiment (col. 7). Records from government registers were 55 percent more likely to be found for patients in biometrics centers (col. 8). This suggests that the introduction of biometric devices reduced the scope for reportedly detecting patients who do not actually seek treatment from that center.

All reported new patients were attempted to be surveyed at least three times. Reportedly new patients in biometrics centers were 25 percent more likely to be found during the research team survey attempts than new patients reported in non-biometrics centers (Panel B, col. 1 and 2). We also record when patients could never be found by the survey team or when health workers asked the team not to visit certain patients. If certain patients are made up by health workers to artificially inflate the number of detections, it is likely that survey attempts would yield one of these two outcomes. Columns 5 and 6 in Panel B show that these cases were significantly more common in centers that were not equipped with biometric devices. Alternatively, newly enrolled patients could be harder to find in control centers because of patient selection issues, i.e. patients enrolled in both groups having significantly different characteristics that make them more difficult to reach. We provide two pieces of evidence against this claim. First, as shown in Table A3 in Appendix, there are only marginal differences between patients selected in biometrics versus non-biometrics centers, not likely to affect the probability of patients to be found for surveying.[4] Second, there is no impact on the probability of finding a patient at the end of their treatment (col. 7 and 8). The devices appear to have improved the accuracy of reporting and reduced the scope for falsifying new patients. When the total number of detections is computed based on independent information on verified patients (whom the survey team could meet), the treatment impact is no longer negative. This suggests that biometric devices reduce the number of misreported

[4] Results in Table A3 show a lower variance in patients' education in biometrics centers than in control centers, as well as more patients with a family history of TB but less relapsing patients.

detections, making the number of new cases seem lower in treatment centers while reflecting more accurate reporting.

5.3 Impact on multitasking

An alternative explanation to the decline in reported detections induced by biometric devices is that of multitasking or strategic allocation of effort. Health workers may focus their effort on the task monitored by the device, namely patient treatment adherence and job attendance, at the expense of new case detection. They may also strategically decrease their detection effort in order to minimize the risks of new patients' interrupting treatment, as a way to limit drop-outs. Table 7 shows the impact of the program on health worker effort towards detection and treatment adherence activities. There is little evidence to support the multitasking hypothesis, as the amount of effort towards detection (measured as a composite index or as the number of different methods employed for detecting new cases) is not significantly lower in the treatment group, maybe because health workers received financial incentives based on detections. The overall level of effort, as measured by a standardized number of hours worked as reported by health workers themselves, is not significantly affected by the program. In line with a reduction of the difficulties health workers in biometrics centers report facing, they are also significantly less likely to report an excessive workload (Panel B col. 3 and 4).

5.4 Impact on health workers' salary and job satisfaction

Table 8 reports estimates of the impact of biometric monitoring on health workers' salary. The monthly salary health workers using biometric devices is 7.6 percent lower than that of their colleagues in the control group. This is a direct consequence of the performance-based monetary incentives that health workers receive, which are partially based on the number of new cases detected. As program data show (Table 6), the number of reported new detections is lower in the treatment group, most likely because health workers can no longer inflate the numbers artificially.

This however does not seem to have a significant impact on their job satisfaction. Whether measured by a standardized index or by a general survey question, there is no significant difference in the level of job satisfaction between the treatment and control groups (col. 2 to 5). The reduction in salary may be compensated by the benefits of having a lower overall workload (see Table 7) or by having the tools to make work less challenging (Table 4). Those results are corroborated by the feedback that health workers in the treatment group provided on the device. For 89 percent of them the device was useful or very useful, and 68 percent of the health workers in digitally equipped centers recommend that the usage of biometric devices be scaled up. Further, 40 percent of the health workers using biometric devices indeed report their skills having improved. The biometric devices may make the job more fulfilling.

6- Additional evidence from qualitative interviews

6.1 Evidence on misreporting

While most health workers provided perfunctory responses to questions on data forgery and misreporting, some (mostly ex-health workers) did elaborate on specific instances. In the following excerpt, one ex-health worker speaks of both the pressure from program managers to meet targets as well as collusion between Operation ASHA staff and DMC staff in falsifying patient detection rates:

Ex-OA health worker: There are things, in the upper level, its working well, but at this level, some people are trying to make it dirty for their selfish motives. Like I am not a TB patient, but they are issuing medicine on my name and misusing it.

Field staff: What happens to the medicine? Is it given to someone else?

Ex- OA health worker: Yes, they throw it or do anything with that.

Research Associate: You have to register the patient at the DMC right?

Ex- OA health worker: Yes but then people have contacts with the people who maintain these registrations at DMC, so that is not an issue.

Research Associate: But the patient has to go to DMC for registration, so they send a fake patient or how do they do this?

Ex- OA health worker: I should not say, they somehow show positive cases…like we have targets…so to maintain the target, even if they requires me to bribe someone, I have to meet the targets. I have to pay from my salary.

Two other ex-health workers also elaborated on instances of patient data falsification in collusion with DMC staff. One ex- health worker mentioned that health workers at his center had “built some connections with lab technicians [at the DMC] to get new patients. They did not want to go for visits so this was an easy way to get patients”. When probed about how the lab technicians got them detections, the ex-counselor replied that “They adjusted it from one to another. Like from my detection they would give few to the other OA health workers. They would also get sputum and give it for testing. I objected that as well as that is not our duty to take sputum. During training it was never said that we need to carry the sputum for testing. They would make slide with the lab technicians as well…They would take their own sputum at times. If they are not going for visits and detection, from where will the sputum come? They suspect name that was given for the daily reporting was also not correct”. Another ex- health worker elaborated that she had heard of similar instances at a DMC where “the TBHV people were in good terms with the OA health workers who went there and they would agree to make patients for them. They would write some name and give them”.

6.2 Evidence on the absence of multitasking

In qualitative interviews, most health workers report spending little effort on detection after having invested time upfront in establishing themselves as DOTS providers in their catchment areas and thus no longer needing to “work very hard” at finding new patients. Their detection activities include door-to-door, current or past patient referrals, referrals from the District Microscopy Centre (DMC), and patients coming to get tested on their own accord, most of those involving little effort. This supports quantitative findings that show lack of evidence for multitasking in response to better monitoring treatment adherence.

Results therefore suggest that the biometric devices improved the accuracy of reporting, and that the apparent drop in the number of detections in the treatment group is partially due to a reduction in forgery of new cases.

7- Conclusion

The DOTS strategy recommended by the WHO to help patients complete their treatment has helped to dramatically improve TB control around the world. It relies on a human-resource intensive system where health workers monitor patients on a daily basis over six months. This paper examines how technological innovation may help alleviate these costs and make the DOTS strategy more cost-effective. While other variations of DOTS are currently being tested, including text messaging and video-DOTS, this study is the first to provide rigorous experimental evidence on the positive impact of biometric monitoring on TB treatment adherence and quality of data reporting.

The experiment was conducted in four states of Northern India, where biometric devices were randomly allocated to pairs of 130 DOTS centers for a duration of one year. We find that the introduction of biometric devices allowing to digitally track TB health workers' attendance at the DOTS center as well as patients' treatment compliance has two major benefits. First, it leads to a significant 20 percent reduction in the number of patients interrupting their treatment. This is likely driven by an improved patient presence at the center as well as improved health worker attendance, effort and productivity, suggesting that the biometric devices are a powerful tool for enforcing the DOTS strategy. Second, keeping biometric records of patients' enrollment and attendance significantly improves the quality of data reported by health workers.

Biometric monitoring serves two pressing objectives of health care policy, especially in developing countries: (i) improving treatment compliance and preventing the development of drug-resistant forms of the disease, (ii) improving the quality of reporting on performance in the health care system.

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Table 1: Health worker summary statistics

	Control group		Treatment group		Full Sample		*P-value* Treatment = Control	Number of obs.
	Mean	SD	Mean	SD	Mean	SD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male	0.78	0.42	0.71	0.46	0.74	0.44	0.49	86
Age	32.11	7.99	29.39	6.29	30.81	7.31	0.04	86
General caste	0.31	0.47	0.51	0.51	0.41	0.49	0.13	86
Hindu	0.73	0.45	0.90	0.30	0.81	0.39	0.07	86
Highest education level achieved								
Other diploma/non-formal education	0.02	0.15	0.02	0.16	0.02	0.15	0.87	86
Class 12 and below	0.58	0.50	0.63	0.49	0.60	0.49	0.44	86
Tertiary	0.36	0.48	0.32	0.47	0.34	0.48	0.57	86
Work experience								
Any previous work experience	0.82	0.39	0.66	0.48	0.74	0.44	0.12	86
Number of years of work experience	8.81	5.45	8.72	4.80	8.77	5.12	0.76	82
Any previous experience in the social/NGO sector	0.18	0.39	0.12	0.33	0.15	0.36	0.25	86
Lives in one of the areas covered by the centers	0.49	0.51	0.63	0.49	0.55	0.50	0.07	85
Assets								
Has electricty	1.00	0.00	0.95	0.22	0.98	0.15	0.08	84
Has tap water	0.67	0.47	0.45	0.50	0.57	0.50	0.01	83
Rents an apartment or house to a third party	0.11	0.32	0.18	0.39	0.14	0.35	0.51	83
Owns land	0.53	0.50	0.47	0.51	0.51	0.50	0.58	85
Exposure to technology								
Knows how to use a computer	0.56	0.50	0.59	0.50	0.57	0.50	0.68	86
Knows how to use the internet	0.45	0.50	0.50	0.51	0.48	0.50	0.93	84
Has an email account	0.44	0.50	0.37	0.49	0.41	0.49	0.59	86
Has a social networking account	0.36	0.48	0.32	0.47	0.34	0.48	0.77	86
Baseline number of detections per month per center[1]	2.96	2.60	2.47	2.02	2.75	2.38	0.13	726
Baseline number of defaults per month per center	0.09	0.37	0.11	0.38	0.10	0.37	0.73	726
Months spent in the experiment	10.06	4.84	10.00	4.85	10.03	4.82	0.73	86

Note : For each variable, we report the means and standard deviations in both the control group, and the treatment group. We also report the p-value of the difference with control for strata fixed effects, and standard errors clustered at the two-center level. The unit of observation is the health worker.

[1] 6 months of per center per month data prior to the experiment was used for both baseline detection and baseline default. The reported p-value comes from a regression clustered at the health worker level.

Table 2: Patient summary statistics

	Full sample			Baseline Sample							
	Mean	SD	Number of obs.	All in baseline sample		Control group		Treatment group		Number of obs.	*P-value* Treatment = Control
				Mean	SD	Mean	SD	Mean	SD		
Panel A: Socio-demographic Characteristics											
Male	0.57	0.49	3408	0.55	0.50	0.53	0.50	0.58	0.49	762	0.41
Age	33.95	16.39	3406	34.09	16.88	33.85	16.99	34.46	16.73	761	0.61
Caste categories											
Doesn't know	0.05	0.21	3410	0.04	0.19	0.04	0.20	0.03	0.16	759	0.35
General caste	0.18	0.38	3410	0.16	0.37	0.16	0.37	0.16	0.37	759	0.67
OBC	0.36	0.48	3410	0.37	0.48	0.37	0.48	0.35	0.48	759	0.40
SC	0.25	0.43	3410	0.25	0.43	0.22	0.41	0.29	0.45	759	0.09
ST	0.08	0.28	3410	0.11	0.32	0.12	0.32	0.11	0.31	759	0.41
Minority	0.09	0.28	3410	0.07	0.26	0.08	0.27	0.06	0.24	759	0.67
Religion											
Hindu	0.86	0.35	3399	0.88	0.32	0.87	0.34	0.90	0.30	756	0.54
Muslim	0.13	0.33	3399	0.10	0.30	0.11	0.32	0.08	0.27	756	-0.63
Other	0.02	0.13	3399	0.02	0.13	0.02	0.14	0.02	0.13	756	0.49
Literacy											
Cannot read or write	0.30	0.46	3412	0.29	0.45	0.27	0.45	0.30	0.46	761	0.48
Can read but not write	0.04	0.19	3412	0.02	0.15	0.02	0.14	0.03	0.16	761	0.88
Can read and write	0.67	0.47	3412	0.69	0.46	0.71	0.46	0.67	0.47	761	0.44
Education											
No schooling	0.22	0.41	3415	0.21	0.41	0.21	0.41	0.21	0.41	763	0.88
Pre-primary	0.02	0.14	2657	0.02	0.12	0.01	0.10	0.02	0.15	599	0.26
Primary	0.49	0.50	2657	0.49	0.50	0.48	0.50	0.50	0.50	599	0.68
Secondary	0.43	0.50	2657	0.45	0.50	0.46	0.50	0.42	0.49	599	0.41
Undergraduate and more	0.06	0.23	2657	0.05	0.22	0.05	0.22	0.06	0.23	599	0.97
Size of the Household	5.58	2.37	3335	5.64	2.36	5.75	2.48	5.46	2.16	749	0.06
Migration Status											
Always lived here	0.50	0.50	3411	0.57	0.50	0.58	0.49	0.56	0.50	762	0.24
Lived here for more than 10 years	0.15	0.36	3411	0.13	0.34	0.13	0.33	0.13	0.34	762	0.52
Lived here for 6 to 10 years	0.09	0.29	3411	0.09	0.29	0.07	0.26	0.12	0.32	762	0.01
Lived here for 1 to 5 years	0.17	0.37	3411	0.15	0.35	0.15	0.35	0.14	0.35	762	0.91
Lived here for less than a year	0.09	0.28	3411	0.07	0.25	0.08	0.26	0.05	0.22	762	0.16
Panel B: Past exposure to TB											
Vaccinated against BCG	0.71	0.45	3027	0.73	0.45	0.73	0.44	0.71	0.45	688	0.31
If vaccinated, mark visible	0.78	0.41	2210	0.78	0.41	0.80	0.40	0.76	0.43	511	0.12
TB history											
has previously had TB	0.26	0.44	3396	0.26	0.44	0.25	0.43	0.28	0.45	759	0.14
num of times the patient had TB previously	0.32	0.62	3390	0.32	0.63	0.28	0.54	0.39	0.75	758	0.02
someone in family had TB since patient was born	0.41	0.49	3386	0.38	0.48	0.34	0.47	0.44	0.50	760	0.00
Panel C: Previous medical consultations											
Consulted someone at least once in past 3 months	0.17	0.38	3402	0.19	0.39	0.20	0.40	0.16	0.37	761	0.24
Facility type											
Private doctor	0.45	0.50	599	0.45	0.50	0.37	0.48	0.61	0.49	144	0.01
Private hospital	0.21	0.41	599	0.19	0.40	0.18	0.39	0.22	0.42	144	0.59
Govt. referral hospital	0.12	0.33	599	0.17	0.37	0.19	0.39	0.12	0.33	144	0.28
Govt. doctor	0.09	0.29	599	0.10	0.31	0.15	0.36	0.02	0.14	144	0.01
Local dispensary	0.06	0.23	599	0.04	0.20	0.06	0.24	0.00	0.00	144	0.01
Others	0.03	0.17	599	0.03	0.18	0.04	0.20	0.02	0.14	144	0.67
Service received (on the 1st visit)											
Medication	0.65	0.48	577	0.58	0.50	0.52	0.50	0.70	0.47	138	0.02
An injection	0.39	0.49	547	0.33	0.47	0.25	0.44	0.47	0.50	138	0.19
A drip	0.13	0.34	526	0.14	0.35	0.13	0.34	0.15	0.36	136	0.54
An Operation	0.04	0.21	512	0.08	0.28	0.10	0.30	0.04	0.21	133	0.10
Estimated amount spent in Rs. (on the 1st visit)	886	2784	572	1220	3668	1338	4131	1002	2625	140	0.20

Notes : The unit of observation is the patient. While for the baseline sample, we only include those patients who were detected by the health worker before our experiment start date, full sample includes all the patients detected during the experiment as well as before the randomization

Table 3: Impact on patient behavior - treatment adherence and patient attendance

Panel A: Impact on treatment adherence

	Treatment interruption (Stopped taking pills)[1]	Missed pills days as a fraction of scheduled visit days	Missed pills at least in one occasion
	(source: patient surveys)	*(source: treatment cards)*	
	(1)	(2)	(3)
Treatment	-0.023	-0.078	-0.159
	(0.009)**	(0.043)*	(0.087)*
Strata fixed effects	Yes	Yes	Yes
Patient controls	Yes	Yes	Yes
Observations	2385	982	660
R-squared	0.094	0.391	0.287
Mean in control group	0.097	0.124	0.433

Panel B: Impact on patient attendance

	Number of patients who visited the center that day	Percentage of scheduled patients who visited the center	Occasionally sent someone else to get the pills		Took medicine for a week or longer duration at the same time	
	(source: random visits)		*(source: patient surveys)*			
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.844	12.934	-0.233	-0.200	-0.069	-0.067
	(0.308)***	(3.263)***	(0.027)***	(0.026)***	(0.022)***	(0.020)***
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes				
Patient controls			Yes	Yes	Yes	Yes
Baseline outcome control				Yes		Yes
Observations	3089	3019	3118	3118	3086	3086
R-squared	0.220	0.119	0.157	0.211	0.087	0.103
Mean in control group	3.107	42.904	0.367	0.367	0.246	0.246

Notes : Standard errors, given in parentheses, are clustered at the two-center level (***, **, * indicate significance at 1, 5 and 10 percent respectively). For Panel A, col. 1, the unit of observation is a patient. In Col. 2 and 3, the unit of observation is a "verified" patient, i.e. a patient whom was successfully administered an entry survey. Patient controls include age, gender, religion, household size, whether the patient had TB in the past and the dummies for the type of patient survey administered (begining of treatment, end of treatment, survey for treatment defaulters, etc). For baseline outcome control in the case of patients of whom we only have exit survey, we imputed the baseline values using the mean of the respective outcome. For Panel B col. 1 and 2, we use a day long monitoring instance as our unit of observation. Health worker controls include age, caste, gender and education of the health worker. In col. 3 to 6, the unit of observation is a patient.

[1]For this outcome, we only consider "exit" or "exit plus" patients, that is patients surveyed at the end or towards the end of their treatment.

Table 4: Impact on health worker behavior - service delivery

Panel A: Impact on absenteeism (source: random visits and spot checks)

	Is health worker present at the center during random check? (extensive margin) *(source: random spot checks)*	Number of hours health worker was present at the center during each shift (intensive margin)[1] *(source: random visits)*	Did anyone from OA come to visit today	Did any manager/ auditor/ supervisor from OA come to visit today
	(1)	(2)	(3)	(4)
Treatment	0.117	0.522	0.056	0.037
	(0.030)***	(0.110)***	(0.014)***	(0.015)**
Strata fixed effects	Yes	Yes	Yes	Yes
Health Worker controls	Yes	Yes	Yes	Yes
Observations	916	2072	2992	2992
R-squared	0.194	0.297	0.130	0.119
Mean in Control Group	0.598	2.008	0.053	0.046

Panel B: Impact on default-related effort and productivity

	Did the health worker make any home visit today	Number of home visits made by the health worker today	# of challenges faced in getting a patient to complete treatment course[2]	
	(source: random visits)		*(source: health worker surveys)*	
	(1)	(2)	(3)	(4)
Treatment	0.029	0.083	-0.648	-0.632
	(0.016)*	-0.059	(0.228)***	(0.216)***
Strata fixed effects	Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes	Yes	Yes
Baseline control				Yes
Observations	3,117	3,117	77	77
R-squared	0.094	0.115	0.307	0.327
Mean in control group	0.156	0.409	3.333	3.333

Panel C: Impact on health worker effort (source: patient surveys)

	Health worker gives advice related to TB		Interaction with health worker increased since treatment[3]	
	(1)	(2)	(3)	(4)
Treatment	0.024	0.023	0.024	0.021
	(0.016)	(0.015)	(0.016)	(0.015)
Strata fixed effects	Yes	Yes	Yes	Yes
Patient controls	Yes	Yes	Yes	Yes
Baseline control		Yes		Yes
Observations	3184	3184	3182	3182
R-squared	0.058	0.068	0.555	0.557
Mean in Control Group	0.895	0.895	0.248	0.248

Notes: Standard errors clustered at the two-center level are in parentheses. ***, **, * indicate significance at 1, 5 and 10%. For Panel A, column 1, the unit of observation is a random spot check by the research team. For Panel A, col. 2 to 4 and Panel B, col. 1-2, we use a day long monitoring visit instance as our unit of observation. For Panel B col. 3-4, the unit of observation is a health worker. For Panel C, the unit of observation is a patient.

The health worker controls include health worker's age, dummies indicating the health worker's education level, whether the health worker belonged to "General caste" category, and whether the health worker was Hindu.

Patient controls include age, gender, religion, household size, whether the patient had TB in the past and the dummies for the kind of patient survey administered (begining of treatment, end of treatment, survey for treatment defaulters, etc).

[1]This outcome is restricted to the health workers who operated out of fixed centers and not mobile catchment areas.

[2]The challenges that the health workers identified were as follows: long duration of treatment (76%), travelling long distance to patient's house to prevent missed dose(33%), patients don't get follow up lab tests done (24%), multiple visits required to counsel patients (37%), patients migrate for long periods at a time during treatment(14%), patients don't consider themselves sick enough and are uncooperative (29%), patients don't believe they have TB and seek private care (19%), gaining patients' trust and convincing them for treatment (48%), low levels of literacy (33%), patients' reluctance to stay on treatment due to loss of work hours (3%).

[3]The patients were asked to gauze the level of their interaction with counselor with the question, "Do you feel your level of interaction with the health worker increased/decreased/remained constant since you first started treatment?"

Table 5: Impact on quality of reporting on treatment adherence

	Reporting on patient default (source: program data)		Pills delivered in monitor's presence (source: random visits)	Pills not delivered in monitor's presence: patient took pills earlier	Pills not delivered in monitor's presence: patient takes pills elsewhere (DMC, private doctor, other)	Pills not delivered: other reasons
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.012	-0.011	0.067	-0.037	-0.023	-0.007
	-0.034	-0.034	(0.035)*	(0.013)***	(0.012)**	(0.034)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Patient controls			Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes				
Baseline outcome		Yes				
Observations	1840	1828	6,873	6,745	6,873	6,873
R-squared	0.037	0.040	0.098	0.025	0.023	0.081
Mean in control group	0.158	0.158	0.670	0.069	0.026	0.237

Notes : Standard errors, in parentheses, are clustered at the two-center level (***, **, * indicate significance at 1, 5 and 10% respectively). Col. 1 and 2 show the impact of biometric devices on the number of defaults, using data from Operation ASHA monthly summary reports filled by health workers. The unit of observation is a health center (or a mobile area) × month. Col. 3 to 6 show impact on pill intake from the random day-long visit data. The unit of observation is a "verified patient" per random spot check. "Verified patients" were patients who we sucessfully administered an entry survey.

Health worker controls include health worker's age, and dummies indicating the health worker's education level, whether the health worker belonged to "General caste" category, and whether the health worker was Hindu.

Baseline default is the average number of default cases per month also calculated over the period of 6 months prior to the intervention for each center.

Table 6: Impact on quality of reporting on patient detection

Panel A: Impact on reported and verified patients

	Reported detections per center per month[6]		Verified detections per center per month		Verified detections per health worker	Haven't met OA health worker/do not take pills from the center		Patient's records not found in government lab registers
	(source: program data)		*(source: patient surveys)*					*(source: govt register data)*
						[verified]	[unverified baseline]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-1.22	-0.926	0.017	0.101	0.571	-0.035	-0.009	-0.036
	(0.323)***	(0.279)***	(0.156)	(0.149)	(4.140)	(0.015)**	-0.015	(0.015)**
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes	Yes	Yes	Yes			
Patient controls						Yes	Yes	Yes
Baseline detection		Yes		Yes				
Observations	1840	1828	1582	1582	80	2071	611	1,452
R squared	0.341	0.393	0.117	0.137	0.495	0.045	0.146	0.063
Mean in control group	3.704	3.704	1.378	1.378	27.500	0.037	0.042	0.065

Panel B: Impact on survey outcomes (source: patients surveys)

	Entry surveys: not completed[1]		Entry Survey: Not completed (Reasons I, II)[2]		Entry Survey: Not completed (Reasons III, IV)		Exit Survey: Not completed (any reason)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.081	-0.051	-0.027	-0.022	-0.044	-0.025	-0.003	-0.014
	(0.025)***	(0.019)***	(0.009)***	(0.009)***	(0.017)***	(0.013)**	(0.020)	(0.017)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance from the center[3]		-0.003		-0.001		0.001		0.004
		-0.004		-0.001		-0.002		-0.004
R-squared	3030	3030	3030	3030	3030	3030	3838	3838
Observations	0.056	0.289	0.009	0.024	0.032	0.268	0.014	0.314
Mean in control group	0.325	0.325	0.078	0.078	0.126	0.126	0.364	0.364

Notes : Standard errors, given in parentheses, are clustered at the two-center level (***, **, * indicate significance at 1, 5 and 10% respectively). Panel A Col. 1 and 2 report the impact on the number of newly detected patients, using data from monthly summary reports filled in by Operation ASHA health workers. In col. 1 to 4, the unit of observation is a health center (or a mobile area) × month. In Col. 5, the unit of observation is a health worker. In col. 6, the unit of observation is a "verified" patient, i.e. a patient who was successfully administered an entry survey. In col. 7, the unit of observation is a "verified patient" whom we were able to locate in the lab register data and whose outcome is supposed to be due assuming 6 months of treatment duration. Indore is excluded from the sample in column 7 as register data are not available. For Panel B, the unit of observation is a unique survey attempt.

The health worker controls include health worker's age, and dummies indicating the health worker's education level, whether the health worker belonged to "General caste" category, and whether the health worker was Hindu. Patient controls include age, gender, religion, household size, whether the patient had TB in the past, and the dummies for the kind of patient survey administered (begining of treatment, end of treatment, survey for treatment defaulters, etc).

Baseline detection is the average number of new patients per month calculated over the period of 6 months prior to the intervention for each center.

[1]This outcome aggregates all the "not completed" cases. The reasons for non-completion include: patient death, patient too ill to be surveyed, patient refused appointment, patient's address could not be located, patient moved out of the address, and health worker warning (in cases where the patients demanded not to be contacted by any third party regarding TB).

[2]Reasons I, II, III, and IV stand for patient refused to answer, patient refused appointment, patient not found, and health working warning respectively.

[3]Distance from the center is the difference between the center location and patient's house location based on the GPS data. When GPS data are missing, the median distance replaces the missing value, which is controlled for in the regression.

Table 7: Impact on heath worker's detection and effort

Panel A: Impact on effort toward patient detection (source: health worker surveys)

	Effort towards detection (quantitative measure)[1]		# of methods used to detect new patients	
	(1)	(2)	(5)	(6)
Treatment	-0.022	-0.028	-0.038	-0.044
	(0.100)	(0.096)	(0.155)	(0.150)
Strata fixed effects	Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes	Yes	Yes
Baseline control		Yes		Yes
Observations	77.000	77.000	76.000	76.000
R-squared	0.748	0.757	0.671	0.678
Mean in control group	-	-	3.513	3.513

Panel B: Impact on overall effort (source: health worker surveys)

	Overall effort[2]		Excessive workload	
	(1)	(2)	(3)	(4)
Treatment	0.008	-0.058	-0.173	-0.179
	(0.230)	(0.202)	(0.088)**	(0.092)*
Strata fixed effects	Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes	Yes	Yes
Baseline control		Yes		Yes
Observations	77	76	77	77
R-squared	0.499	0.608	0.576	0.577
Mean in control group			0.359	0.359

Notes: Standard errors clustered at the two-center level are in parentheses. ***, **, * indicate significance at 1, 5 and 10%. Strata fixed effects constitute sample cities interacted with the health worker type (center based, mobile, or hybrid). We take a health worker as the unit of observation and include all health workers whose endline, or midline, survey was done. The health worker controls include health worker's age, religion, whether she belongs to general caste, and dummies indicating the health worker's education level. In few cases of missing values for baseline controls, we imputed the baseline values using the mean of the respective outcome.

[1]Effort towards detection is a standarized index composite of number of sputum samples of TB suspects sent to the lab last week, and number of days spent detecting new patients last week.

[2]Overall effort is a standarized index of the number of hours the health worker reported to have worked per day on average.

Table 8: Impact on health workers' salary and job satisfaction

	Monthly salary (Op ASHA reported)		Standardized job satisfaction index[1]		Overall satisfied with job	
	(1)		(2)	(3)	(4)	(5)
Treatment	-444	-	0.082	0.132	0.057	0.065
	(190.157)**	-	(0.106)	(0.106)	(0.093)	(0.096)
City fixed effects	Yes	-	Yes	Yes	Yes	Yes
Health worker controls[2]	Yes	-	Yes	Yes	Yes	Yes
Baseline control				Yes		Yes
Observations	923	-	76	77	76	77
R-squared	0.491	-	0.478	0.485	0.266	0.279
Mean in control group	5837	-	-	-	0.795	0.795

Notes : ***, **, * indicate significance at 1, 5 and 10%. Standard errors, clustered at the two-center level, are in parentheses. For column 1: we take a health worker per month into the experiment as the unit of observation and include all health workers in the experiment. For columns 2-5: we take a health worker as the unit of observation. In few cases of missing values for baseline controls, we imputed the baseline values using the mean of the respective outcome.

[1]The standarized job satisfaction index is composite of satisfaction with respect to the compensation, overall satisfaction with work, and whether the health worker has recommended her job to someone else in the past 6 months.

[2]The health worker controls include health worker's age, and dummies indicating caste, religion, and health worker's education level.

Table A1: Impact on health worker attrition

	Health worker dropped out during the intervention	
	(1)	(2)
Treatment	0.046	-0.036
	(0.074)	(0.080)
Strata fixed effects:		
Bhopal (center)	0.125	0.024
Bhopal (mobile)	0.207	-0.04
Gwalior (center)	0.199	-0.151
Gwalior (mobile)	0.670**	0.316
Gwalior (hybrid)	0.489***	0.019
Indore (center)	0.111	-0.111
Sagar (center)	0.425**	0.488***
Sagar (hybrid)	0.784***	0.610***
Delhi (center)	0.670***	0.916***
Raipur (center)	0.236*	0.128
Durg/Bhilai (center)	0.511***	0.333
Korba (center)	0.178	0.007
Bhubaneswar (center)	0.207	0.131
Bhubaneswar (mobile)	0.034	-0.273
age		-0.006
gender (male)		0.464***
religion (Hindu)		0.206*
educational level		
other diploma/non-formal		-0.395
twelve and below		-0.075
under three years of university		-0.122
work experience before OA		-0.315***
pre-exposure to technology		-0.049
baseline performance		
number of detections past month		-0.001
number of default prevention activities		0.075
remembers last patient sent for sputum testing		0.092
baseline motivation		
joined OA for social cause		0.059
recommended OA to someone in past 6 months		-0.083
Observations	86	82
R-squared	0.23	0.439
Mean in Control Group	0.267	0.267

Notes : Robust standard errors are in parentheses. ***, **, * indicate significance at 1, 5 and 10%. We take a health worker as the unit of observation and include all health workers who were part of the experiment.

Table A2: Attrition check of the health workers

	Mean in initial sample [SD]	Mean in attritor sample [SD]	Mean in replacement sample [SD]	Mean in final sample [SD]	Difference between initial and final sample (s.e.)
	(1)	(2)	(3)	(4)	(5)
Male	0.754	0.875	0.714	0.744	-0.023
	[0.434]	[0.338]	[0.463]	[0.439]	(0.072)
Age	31.75	29.21	27.90	30.81	-4.974
	[7.211]	[9.418]	[7.014]	[7.314]	(1.848)***
General caste	0.385	0.375	0.476	0.407	0.108
	[0.490]	[0.495]	[0.512]	[0.494]	(0.095)
Hindu	0.831	0.875	0.762	0.814	-0.082
	[0.378]	[0.338]	[0.436]	[0.391]	(0.088)
Highest education level achieved					
Other diploma/non-fo	0.0323	0.000	0.000	0.0241	-0.027
	[0.178]	[0.000]	[0.000]	[0.154]	(0.021)
Class 12 and below	0.645	0.652	0.571	0.627	0.031
	[0.482]	[0.487]	[0.507]	[0.487]	(0.118)
Some tertiary educati	0.323	0.348	0.429	0.349	-0.004
	[0.471]	[0.487]	[0.507]	[0.480]	(0.116)
Work experience					
Any previous work exp	0.738	0.667	0.762	0.744	-0.042
	[0.443]	[0.482]	[0.436]	[0.439]	(0.112)
Number of years of wo	8.984	9.783	8.143	8.768	-0.252
	[5.239]	[4.572]	[4.830]	[5.121]	(1.505)
Any previous experien	0.169	0.000	0.0952	0.151	-0.016
	[0.378]	[0.000]	[0.301]	[0.360]	(0.074)
Lives in one of the areas	0.615	0.417	0.350	0.553	-0.242
	[0.490]	[0.504]	[0.489]	[0.500]	(0.134)*
Assets					
Has electricty	0.968	0.957	1.000	0.976	0.052
	[0.177]	[0.209]	[0.000]	[0.153]	(0.041)
Has tap water	0.500	0.826	0.762	0.566	0.059
	[0.504]	[0.388]	[0.436]	[0.499]	(0.121)
Rents an apartment or	0.159	0.0455	0.100	0.145	-0.05
	[0.368]	[0.213]	[0.308]	[0.354]	(0.087)
Owns land	0.516	0.696	0.476	0.506	-0.012
	[0.504]	[0.470]	[0.512]	[0.503]	(0.139)
Exposure to technology					
Knows how to use a co	0.538	0.708	0.667	0.570	-0.006
	[0.502]	[0.464]	[0.483]	[0.498]	(0.141)
Knows how to use the	0.429	0.696	0.619	0.476	0.066
	[0.499]	[0.470]	[0.498]	[0.502]	(0.112)
Has an email account	0.354	0.500	0.571	0.407	0.169
	[0.482]	[0.511]	[0.507]	[0.494]	(0.142)
Has a social networkin	0.292	0.542	0.476	0.337	0.126
	[0.458]	[0.509]	[0.512]	[0.476]	(0.097)
Months spent in the exp	11.17	4.330	6.494	10.03	-2.368
	[4.508]	[4.263]	[4.019]	[4.816]	(1.098)**
Observations	65	24	21	86	86

Note: In col 5, we report the difference between initial and final sample as obtained from the OLS regression controlling for strata fixed effects; robust standard errors are in parentheses.

Initial sample = health workers in the sample when the experiment started.

Replacement health workers = health workers who entered the sample over the course of the experiment.

Table A3: Impact on patient selection

Panel A: Patient profile	Gender	Age	Caste: Does not know	Caste: General	Caste: Other backward classes	Caste: Scheduled caste	Caste: Scheduled tribe	Caste: Minority (Muslim, Christian)	Religion: Hindu	Religion: Muslim	Religion: Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Treatment	-0.018	-1.387	0.003	-0.017	-0.005	0.046	-0.012	-0.014	0.03	-0.023	-0.007
	(0.020)	(0.795)*	(0.010)	(0.022)	(0.025)	(0.030)	(0.015)	(0.030)	(0.035)	(0.036)	(0.006)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2621	2620	2626	2626	2626	2626	2626	2626	2619	2619	2619
R squared	0.022	0.025	0.018	0.066	0.062	0.038	0.114	0.130	0.080	0.086	0.042
Mean in control group	0.586	34.490	0.048	0.181	0.358	0.232	0.078	0.104	0.833	0.146	0.020

Panel B: Literacy and education	Cannot read or write	Can read but not write	Can read and write	Education: No schooling	Education: Pre-primary	Education: Primary	Education: Secondary	Education: Undergraduate and more
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.02	0.013	0.007	-0.034	0.003	0.045	-0.022	-0.026
	(0.021)	(0.009)	(0.023)	(0.018)*	(0.007)	(0.026)*	(0.026)	(0.013)**
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2626	2626	2626	2627	2039	2039	2039	2039
R squared	0.022	0.057	0.029	0.028	0.022	0.025	0.024	0.021
Mean in control group	0.303	0.043	0.655	0.227	0.021	0.479	0.436	0.064

Panel C: Household information, TB history, and previous medical consultations	Size of the Household	Vaccinated against BCG	Has previously had TB	Num of times the patient had TB previously	Someone in family had TB since patient was born	At least one non-DOTS related consultation in past 3 months
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.187	0.011	-0.028	-0.042	0.068	0.017
	(0.102)*	(0.019)	(0.016)*	(0.023)*	(0.023)***	(0.014)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2562	2315	2612	2607	2602	2616
R squared	0.020	0.021	0.035	0.038	0.026	0.123
Mean in control group	5.641	0.706	0.270	0.332	0.403	0.174

Notes: Standard errors, given in parentheses, are clustered at the two-center level (***, **, * indicate significance at 1, 5 and 10 percent respectively).We take a patient as the unit of observation, excluding the patients who were enrolled in treatment prior to randomization date.

Table A4: Impact on final outcome (Data source: government lab registers)

	Default[1]	Treatment complete	Cured	Patient death	Failure	Transfer out	Patient turned MDR	Patient's sputum not positive	Treatment running	Final treatment outcome not available	Patient's records not found
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Treatment	0.051	-0.037	0.002	-0.01	-0.006	0.004	0.001	-0.006	0.004	0.033	-0.036
	(0.048)	(0.032)	(0.025)	(0.009)	(0.006)	(0.002)**	(0.002)	(0.021)	(0.003)	(0.033)	(0.015)**
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,452	1,452	1,452	1,452	1,452	1,452	1,452	1,452	1,452	1,452	1,452
R-squared	0.067	0.113	0.066	0.020	0.016	0.010	0.017	0.117	0.100	0.070	0.063
Mean in control group	0.135	0.331	0.184	0.025	0.013	0.000	0.001	0.053	0.006	0.186	0.065

Notes: Clustered standard errors are given in parentheses. ***, **, * indicate significance at 1, 5 and 10% respectively. The unit of observation is a "verified patient" whose we were able to locate in the lab register data and whose outcome is supposed to be due assuming 6 months of treatment duration. We define verified patients as patients for whom we sucessfully managed to do their entry survey. The observations only account for 8 cities in the experiment since we could not acquire the administrative data from one city in the experiment.

In addition to those patients whose default status was explicit in the data, we considered all those patients as defaulters whose treatment outcome along with their last three lab test information was missing from the TB register. Similarly, for patients whose all four lab tests are completed indicating the end of a regular treatment schedule, we consider them in the "Treatment Complete" category.