Making Incentives Work: Biometric Monitoring Improves Healthcare Provision and Reduces Misreporting

Experimental Evidence from Tuberculosis Control in India[1]

Thomas BOSSUROY Clara DELAVALLADE Vincent PONS

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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.

[1] Bossuroy: World Bank, tbossuroy@worldbank.org; Delavallade: IFPRI, c.delavallade@cgiar.org; Pons: Harvard Business School, vpons@hbs.edu. We thank seminar participants at the Harvard Development Faculty Retreat, the GREThA International Conference on Economic Development and the Duke University and Hewlett Foundation Workshop on Quality of Healthcare. Siddhartha Baral, Sruthi Chandrasekaran, Sadish Dhakal, Chand Mazumdar and Mansi Shah for field management and research assistance. This project was funded by grants from USAID, AusAid and the Health Results Innovations Trust Fund administered by the World Bank. The views expressed in this paper do not represent those of the World Bank. All errors are ours.

Labor markets in developing countries are particularly subject to frictions including asymmetric information regarding workers motivation and effort. If effort is not directly observable, workers might decide to shirk to lower effort cost. Moral hazard dampens the quality of service delivered by frontline providers in social sectors, especially in developing countries where low government capacity makes monitoring and data reporting difficult. A growing body of evidence documents that poor performance of health care in low and middle income countries is due not only to inadequate training or knowledge deficiencies but also to insufficient provider effort, translating into high absenteeism rates (Chaudhury and Hammer 2004, Banerjee et al. 2004).

Poor service delivery plagues efforts to control the spread of Tuberculosis (henceforth TB). About one thousand Indians die of TB every single day. As a comparison, as many lives are lost to TB in twelve days in India as during the entire 2014-2015 Ebola outbreak. Cheap, widely available drugs exist to cure the vast majority of TB cases. One of the biggest challenges to contain the spread of the disease is to ensure that patients complete the entire course of the six-month treatment. Treatment adherence is made difficult by remoteness, drug side effects, and commitment issues as symptoms of the disease disappear after a few weeks of treatment. Fighting TB is essentially a service delivery challenge, and health workers may play a crucial role in addressing it if they have adequate work incentives.

While in the presence of asymmetric information, effective monitoring has been shown to reduce shirking, bolster workers effort and productivity and align principals and agents incentives [Akerlof and Yellen, 1986, Fehr et al., 2007], attempts to strengthen incentives in the healthcare system with stronger monitoring and performance reporting have shown poor results in the past (Duflo and Hanna 2005, Banerjee et al. 2008).

This paper examines the benefits of leveraging two technological advances for reducing agency problems and improving 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. 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 misreporting; 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. The intervention aimed to improve health workers' productivity by lowering the cost of monitoring patients' pill intake, increase their effort through higher attendance at the treatment centers, and enhance the quality of performance reporting on which incentives are based. Results were analyzed based on a unique dataset built through the matching and merging of several separate data: several rounds of survey data collected from patients and health workers, program data collected from the NGO, administrative data collected from government hospitals and laboratories, and monitoring data collected independently.

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.

This paper contributes to the small but growing literature on technology and service delivery. 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 to improve health worker's adherence to guidelines for malaria treatment (Zurovac et al., 2011). 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. The use of biometric devices for TB control was studied through qualitative beneficiary surveys

(Bhatnagar et al. 2012) and observational studies (Snidal et al. 2015). This paper innovates in using a randomized design to solve selection issues and rigorously quantify the impact of the technology. Outside of the health sector, 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).

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 program and experimental setup, Section 3 the data. Section 4 presents samples and balance checks. Section 5 describes the estimation strategy. Quantitative results are presented in Section 6, qualitative results in Section 7. Section 8 concludes.

1- Background – 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.

2- E-compliance program and experimental design

2.1. 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]

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[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.

2.2 Experimental setup

The experiment was rolled out sequentially in Northern India, across nine cities in four states - Madhya Pradesh, Delhi, Chhattisgarh and Odisha - between mid-March and mid-September 2013. The study duration spanned an average of 13 months in each city. In these cities' slums, Operation ASHA was contracted by the government to run TB treatment catchment areas, either through health workers appointed in DOTS centers or through mobile health workers. Catchment areas were grouped into clusters of two, either with two centers run by one fixed health worker, spending every other day in a given center, or with one mobile health worker. The randomization was done at the cluster level in strata defined separately for each city and type of cluster (fixed or mobile counselors). 18 to 32 days after randomization, biometric devices were installed in the treatment centers or provided to mobile counselors. 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.

Catchment areas were scattered enough not to overlap. In addition health workers were permanently assigned to their catchment areas, limiting the scope for interactions between health workers of different treatment groups and for other spill-over effects.

Selection criteria for a replacement health worker included living in the catchment area, which limits the possibility of worker allocation correlating with a catchment area treatment status. In addition, employee turnover was handled rapidly, with departing health workers being replaced on the day of their departure oftentimes and within 8 days on average. In one case, the health worker was not replaced because the departure occurred within one moth of the end of the experiment. In order to allow for a rapid replacement of health workers terminating their contract, employee selection was based on a waitlist of existing ranked applicants, limiting the risk of selection of replacements based on characteristics potentially correlating both treatment status and outcomes.

The total sample comprises 65 clusters spanning 131 catchment areas. 52 clusters were center-based, 7 were clusters of mobile health workers and 6 were hybrid clusters: 31 treatment clusters and 34 control clusters. Among the 65 clusters, 62 spanned two catchment areas, 1 spanned only one area and 2 clusters spanned 3 catchment areas.

Catchment areas in the sample were operated by a total of 85 health workers, with an average of 1.3 health workers per cluster: 41 health workers in treatment clusters, 44 health workers in control clusters. On average, each health worker remained 309 days in the experiment

3- **Outcomes of interest: data sources and measurement**

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.

3.1 Data sources

Survey data

Patient sampling was conducted on 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 (based on OA monthly reports). The full sample comprises 4911 patients undergoing treatment in any of the 131 DOTS centers under experiment over the course of the experiment. The full sample comprises 4911 patients in the patient roster for whom data was collected either through patient surveys, treatment cards or random visits, as well as program data.

To assess the impact of the program on treatment adherence, we rely on data from extensive quantitative surveys collected throughout the course of the experiment with 3393 **patients**. In 35% of cases, patients were surveyed twice: once at the onset of their treatment (entry), once after they completed their treatment (exit). Most patients were interviewed at home. Three attempts were made to locate the patient before they were declared “Not found”. The outcome of these survey attempts is used to measure quality of reporting on patient detection. The patient questionnaire also collects information on interactions with health care providers which is used to measure health worker effort put towards patient adherence to treatment.

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’ effort, motivation and work satisfaction as well as interactions with patients and with OA. For health workers who quit OA during the intervention, an additional module investigated the motivations for employment termination.

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' attendance and effort, i.e. 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. Overall, 85.6 percent of patients in the full sample have at least one random visit observation. On average, each patient has 3.7 random visit observations.

Random spot checks

In addition to the day-long monitoring visits conducted by assigned monitors, our senior field staff conducted independent random checks of the Op ASHA centers to get a snapshot of the center's functioning during the intervention period and provide an additional measure of health worker attendance at the center. These visits lasted for five to ten minutes during which the field staff noted information such as whether the center was open, whether the health was present, and whether there were any patients in the center. On average, the rate of random check visit was 0.64 visit per center per month.

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.

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. We use the discrepancy between the number of detections reported in the monthly NGO data and the number of patients successfully administered an entry survey as a proxy for the quality of reporting on patient detection. In addition, we cross-check program data on patient defaults with pill delivery as recorded during our bi-monthly random visits and thereby approximate the quality of reporting on patient adherence to treatment.

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.[4] 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. We use government data in a similar manner as we use program data, in combination with independent data to measure the quality of reporting.

Treatment cards are maintained by Operation ASHA health workers.[5] Each newly enrolled patient is assigned a treatment card that contains detailed information about daily treatment adherence, type of TB and sputum test results. Treatment cards were also used to collect the date when patients started their treatment. Treatment start date is crucial to determine whether a patient was detected prior to the onset of the experiment or after and thus to distinguish selection and treatment effects. Over the course of the experiment, patients with characteristics correlated with outcomes may have been detected and thus started treatment as a result of the intervention, inducing selection of patients entering the sample. Overall, information on treatment start date was retrieved for 99.8 percent of patients from either of three sources: patient rosters collected to sample patients to survey, patient surveys or treatment cards.

3.2 Data merges

Data sources were merged using patients' TB number, lab number, name and treatment center. Each merge was verified manually.

[4] TB and lab registers were collected in all cities under experiment, with the exception of Indore where the research team did not get permission to access lab registers. We were able to find and match government and patient survey data for 83.3 percent of the patients we surveyed, 93.7 percent of patients on the subset of patients excluding Indore.

[5] Treatment cards are uniform across India, supplied by the RNTCP. One copy is kept by the patient, one at the DOTS center, and one at the nearest public hospital.

4- Sample Description and Balance Checks

4.1 Health workers

Our sample comprises 131 DOTS centers in Madhya Pradesh, Delhi, Chhattisgarh and Odisha. These centers were operated by a total of 87 Operation ASHA health workers, 42 in the treatment group, 45 in the control group, . This includes 66 health workers hired at the onset of the experiment and 21 health workers replacing those leaving. 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 community health workers in the initial sample, separated by treatment status, 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, 54 percent know how to use a computer and 33 percent have an email account. Further, out of the 20 characteristics tested, only one – whether or not health worker had previous work experience – has significantly different means across treatment and control groups (at the 5 percent level), what would be statistically expected from successful random assignment.

4.2 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 of patients in treatment during the experiment,, who were detected and enrolled in DOTS centers before the onset of (resp. during) the experiment in Table 2a (resp. Table 2b). Both samples display very similar characteristics. 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 tables 2a and 2b reports the *p-value* of the test that the difference between means in the control group and in the treatment group is null. In Table 2a, the sample of patients is restricted to those enrolled in the DOTS centers prior to the onset of the experiment. The test results therefore display information on baseline balancing test. 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. In Table 2b, the sample of patients includes all patients attending DOTS centers during the experiment, enrolled prior to and during the experiment. Thus, test imbalance may reflect either baseline or selection imbalance. The full set of patients shows very limited imbalance on observable characteristics.

5- 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:

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

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:

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

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:

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

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.

6- Quantitative Results

6.1 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 2.2 percentage points less likely to interrupt their treatment before its completion[6], a 23 percent increase to the 9.6 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

[6] Patients were asked whether they had completed a full course of TB medication and given the choice between three responses: "Yes", "No I am still taking pills", "No I stopped taking pills".

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, 29.1 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 (Table 1). In addition, the share of scheduled patients who actually visited the center on the day they were supposed to is 30.5 percent higher in centers equipped with biometric devices (col. 2). Further, patients in the treatment group are 22.4 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). They also are 4 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. 4). 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 59.8 percent. This probability reaches 72.1 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 33 minutes per shift (half-day), a 27.5 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 3.5 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 extensively and intensively (Panel B, col. 1 and 2), although only the increase on the extensive margin is significant at the 5 percent level. 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 despite being more likely to interact with them (Panel C).

6.2 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 31 percent 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). Records from government registers were 55 percent more likely to be found for patients in biometrics centers (col. 7). 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.[7] 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 detections, making the number of new cases seem lower in treatment centers while reflecting more accurate reporting.

6.3 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).

6.4 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 6.7 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

[7] 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.

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.

7- Additional evidence from qualitative interviews

7.1 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 require 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".

7.2 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 improve 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.

8- 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		*P-value* Treatment = Control	Number of obs.
	Mean	SD	Mean	SD		
	(1)	(2)	(3)	(4)	(5)	(6)
Male	0.794	0.41	0.71	0.461	0.382	65
Age	33.382	7.82	30.387	6.065	0.097	65
General caste	0.265	0.448	0.516	0.508	0.059	65
Hindu	0.765	0.431	0.903	0.301	0.148	65
Highest education level achieved						
Other diploma/non-formal education	0.029	0.171	0.032	0.18	0.936	65
Class 12 and below	0.647	0.485	0.613	0.495	0.851	65
Tertiary	0.265	0.448	0.323	0.475	0.676	65
Work experience						
Any previous work experience	0.853	0.359	0.645	0.486	0.038	65
Number of years of work experience	9.188	5.716	8.724	4.72	0.749	61
Any previous experience in the social/NGO sector	0.206	0.41	0.133	0.346	0.548	64
Lives in one of the areas covered by the centers	0.563	0.504	0.733	0.45	0.142	62
Assets						
Has electricty	1	0	0.933	0.254	0.104	63
Has tap water	0.594	0.499	0.4	0.498	0.112	62
Rents an apartment or house to a third party	0.118	0.327	0.207	0.412	0.232	63
Owns land	0.559	0.504	0.483	0.509	0.626	63
Exposure to technology						
Knows how to use a computer	0.559	0.504	0.516	0.508	0.725	65
Knows how to use the internet	0.424	0.502	0.433	0.504	0.962	63
Has an email account	0.412	0.5	0.258	0.445	0.168	65
Has a social networking account	0.294	0.462	0.258	0.445	0.663	65
Baseline number of detections per month per center[1]	2.96	2.60	2.47	2.02	0.13	726
Baseline number of defaults per month per center	0.09	0.37	0.11	0.38	0.73	726
Months spent in the experiment	350.029	127.961	333.226	138.933	0.625	65

Note : Sample includes all health workers present at the onset of the experiment. 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 2a: Patient summary statistics

	Control group		Treatment group		*P-value* Treatment = Control	Number of obs.
	Mean	SD	Mean	SD		
Panel A: Socio-demographic Characteristics						
Male	0.535	0.499	0.576	0.495	0.542	789
Age	34.04	16.77	34.311	16.61	0.856	788
Caste categories						
Doesn't know	0.04	0.196	0.026	0.159	0.51	786
General caste	0.16	0.367	0.165	0.371	0.533	786
OBC	0.376	0.485	0.352	0.478	0.652	786
SC	0.229	0.421	0.297	0.458	0.101	786
ST	0.118	0.323	0.103	0.305	0.153	786
Minority	0.078	0.268	0.058	0.234	0.528	786
Religion						
Hindu	0.869	0.337	0.903	0.297	0.529	783
Muslim	0.112	0.315	0.081	0.274	0.622	783
Other	0.019	0.136	0.016	0.127	0.47	783
Literacy						
Cannot read or write	0.271	0.445	0.301	0.459	0.439	788
Can read but not write	0.021	0.143	0.026	0.159	0.946	788
Can read and write	0.708	0.455	0.673	0.47	0.411	788
Education						
No schooling	0.208	0.407	0.218	0.413	0.934	788
Pre-primary	0.008	0.091	0.016	0.127	0.338	788
Primary	0.375	0.485	0.39	0.488	0.538	788
Secondary	0.367	0.482	0.334	0.473	0.469	788
Undergraduate and more	0.042	0.2	0.042	0.201	0.916	788
Size of the Household	4.726	2.457	4.505	2.233	0.109	775
Migration Status						
Always lived here	0.57	0.496	0.542	0.499	0.304	789
Lived here for more than 10 years	0.136	0.343	0.145	0.353	0.626	789
Lived here for 6 to 10 years	0.073	0.261	0.113	0.317	0.002	789
Lived here for 1 to 5 years	0.146	0.354	0.148	0.356	0.814	789
Lived here for less than a year	0.075	0.264	0.052	0.222	0.16	789
Panel B: Past exposure to TB						
Vaccinated against BCG	0.739	0.44	0.725	0.448	0.318	713
If vaccinated, mark visible	0.799	0.401	0.762	0.427	0.165	535
TB history						
has previously had TB	0.256	0.437	0.282	0.45	0.141	786
num of times the patient had TB previously	0.292	0.54	0.392	0.772	0.012	785
someone in family had TB since patient was born	0.343	0.475	0.424	0.495	0.006	787
Panel C: Previous medical consultations						
Consulted someone at least once in past 3 months	0.209	0.407	0.161	0.368	0.085	788
Facility type						
Private doctor	0.356	0.481	0.58	0.499	0.007	151
Private hospital	0.188	0.393	0.24	0.431	0.95	151
Govt. referral hospital	0.188	0.393	0.14	0.351	0.419	151
Govt. doctor	0.149	0.357	0.02	0.141	0.01	151
Local dispensary	0.059	0.238	0	0	0.023	151
Others	0.059	0.238	0.02	0.141	0.341	151
Service received (on the 1st visit)						
Medication	0.541	0.501	0.66	0.479	0.13	145
An injection	0.247	0.434	0.458	0.504	0.097	145
A drip	0.126	0.334	0.149	0.36	0.728	142
An Operation	0.096	0.296	0.043	0.206	0.07	140
Estimated amount spent in Rs. (on the 1st visit)	1168	3898	987.2	2600	0.302	146

Notes : Sample includes patients detected before the onset of the experiment, in treatment during the experiment. The unit of observation is the patient.

Table 2b: Patient summary statistics

	Baseline sample					
	Control group		Treatment group		*P-value* Treatment = Control	Number of obs.
	Mean	SD	Mean	SD		
Panel A: Socio-demographic Characteristics						
Male	0.573	0.495	0.576	0.494	0.767	3,387
Age	34.32	16.48	33.365	16.22	0.15	3,385
Caste categories						
Doesn't know	0.046	0.21	0.047	0.212	0.959	3,388
General caste	0.176	0.381	0.176	0.381	0.902	3,388
OBC	0.361	0.481	0.352	0.478	0.86	3,388
SC	0.23	0.421	0.273	0.446	0.085	3,388
ST	0.088	0.283	0.077	0.266	0.167	3,388
Minority	0.098	0.297	0.075	0.263	0.46	3,388
Religion						
Hindu	0.841	0.366	0.877	0.329	0.366	3,377
Muslim	0.139	0.346	0.11	0.312	0.486	3,377
Other	0.02	0.141	0.014	0.117	0.181	3,377
Literacy						
Cannot read or write	0.296	0.457	0.296	0.456	0.665	3,390
Can read but not write	0.037	0.189	0.04	0.196	0.596	3,390
Can read and write	0.667	0.472	0.665	0.472	0.852	3,390
Education						
No schooling	0.224	0.417	0.209	0.407	0.092	3,381
Pre-primary	0.015	0.122	0.019	0.135	0.271	3,381
Primary	0.372	0.483	0.406	0.491	0.051	3,381
Secondary	0.341	0.474	0.327	0.469	0.781	3,381
Undergraduate and more	0.047	0.212	0.04	0.196	0.221	3,381
Size of the Household	4.661	2.488	4.474	2.183	0.026	3,313
Migration Status						
Always lived here	0.523	0.5	0.475	0.5	0.146	3,389
Lived here for more than 10 years	0.138	0.345	0.165	0.371	0.066	3,389
Lived here for 6 to 10 years	0.085	0.279	0.102	0.302	0.088	3,389
Lived here for 1 to 5 years	0.165	0.372	0.172	0.377	0.669	3,389
Lived here for less than a year	0.089	0.285	0.087	0.281	0.764	3,389
Panel B: Past exposure to TB						
Vaccinated against BCG	0.714	0.452	0.714	0.452	0.785	3,006
If vaccinated, mark visible	0.786	0.41	0.776	0.417	0.207	2,197
TB history						
has previously had TB	0.266	0.442	0.254	0.435	0.698	3,374
num of times the patient had TB previously	0.321	0.609	0.313	0.635	0.893	3,368
someone in family had TB since patient was born	0.388	0.487	0.444	0.497	0.003	3,364
Panel C: Previous medical consultations						
Consulted someone at least once in past 3 months	0.184	0.387	0.165	0.372	0.324	3,381
Facility type						
Private doctor	0.444	0.498	0.469	0.5	0.25	597
Private hospital	0.202	0.402	0.22	0.415	0.491	597
Govt. referral hospital	0.121	0.326	0.124	0.331	0.891	597
Govt. doctor	0.098	0.298	0.083	0.276	0.818	597
Local dispensary	0.067	0.251	0.037	0.19	0.216	597
Others	0.067	0.251	0.066	0.249	0.935	597
Service received (on the 1st visit)						
Medication	0.638	0.481	0.674	0.47	0.42	576
An injection	0.362	0.481	0.43	0.496	0.096	546
A drip	0.127	0.333	0.139	0.347	0.526	524
An Operation	0.05	0.218	0.038	0.192	0.131	511
Estimated amount spent in Rs. (on the 1st visit)	909.1	3166	807.36	1987	0.546	571

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	-0.022	-0.078	-0.159
	(0.009)**	(0.043)*	(0.087)*
Strata fixed effects	Yes	Yes	Yes
Patient controls	Yes	Yes	Yes
Observations	2,425	982	660
R-squared	0.037	0.391	0.287
Mean in control group	0.096	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: monitoring visits)		*(source: patient surveys)*	
	(1)	(2)	(3)	(4)
Treatment	0.906	0.131	-0.224	-0.042
	(0.313)***	(0.033)***	(0.025)***	(0.020)**
Strata fixed effects	0.000	0.000	Yes	Yes
Health worker controls	Yes	Yes		
Patient controls	Yes	Yes	Yes	Yes
Observations	3,089	3,019	4,295	4,260
R-squared	0.215	0.118	0.146	0.078
Mean in control group	3.107	0.429	0.359	0.219

Notes : Sample includes all patients undergoing treatment during experiment, enrolled either prior to or during the experiment. 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: monitoring and random visits)

	Is health worker present at the center during random check? (extensive margin)	Number of hours health worker was present at the center during each shift (intensive margin)[1]	Did anyone from OA come to visit today	Did any manager/ auditor/ supervisor from OA come to visit today
	(source: random visits)		*(source: monitoring visits)*	
	(1)	(2)	(3)	(4)
Treatment	0.123	0.553	0.052	0.035
	(0.031)***	(0.112)***	(0.015)***	(0.015)**
Strata fixed effects	Yes	Yes	Yes	Yes
Health Worker controls	Yes	Yes	Yes	Yes
Observations	916	2,072	2,992	2,992
R-squared	0.188	0.291	0.125	0.114
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: monitoring visits)		*(source: health worker surveys)*	
	(1)	(2)	(3)	(4)
Treatment	0.036	0.097	-0.612	-0.585
	(0.016)**	(0.058)	(0.260)**	(0.244)**
Strata fixed effects	Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes	Yes	Yes
Baseline control				Yes
Observations	3,117	3,117	76	76
R-squared	0.092	0.114	0.303	0.322
Mean in control group	0.156	0.409	3.316	3.316

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)
Treatment	0.014	0.025
	(0.016)	(0.015)*
Strata fixed effects	Yes	Yes
Patient controls	Yes	Yes
Observations	4,401	4,389
R-squared	0.050	0.515
Mean in Control Group	0.894	0.260

Notes: Standard errors clustered at the two-center level are in parentheses. ***, **, * indicate significance at 1, 5 and 10%. For Panel A and B, samples include patients detected prior to the onset of the experiment. For Panel C, sample includes patients detected prior to and during the experiment. For Panel A, column 1, the unit of observation is a random visit by the research team. For Panel A, col. 2 to 4 and Panel B, col. 1-2, we use a day long monitoring 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 gauge 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		Pills delivered in monitor's presence	Pill not delivered in monitor's presence: patient took pills earlier	Pill not delivered in monitor's presence: patient takes pills elsewhere (DMC, private doctor, other)	Pills not delivered: other reasons
	(source: program data)			*(source: monitoring visits)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.011	0.014	0.067	-0.037	-0.023	-0.007
	(0.033)	(0.032)	(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	1,839	1,827	6,873	6,745	6,873	6,873
R-squared	0.037	0.050	0.098	0.025	0.023	0.081
Mean in control group	0.156	0.156	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 process monitoring data. The unit of observation is a "verified patient" per random visit. "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]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-1.143	-0.829	0.017	0.101	0.571	-0.035	-0.036
	(0.320)***	(0.281)***	(0.156)	(0.149)	(4.140)	(0.015)**	(0.015)**
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes	Yes	Yes	Yes		
Patient controls						Yes	Yes
Baseline detection		Yes		Yes			
Observations	1,839	1,827	1,582	1,582	80	2,071	1,452
R squared	0.332	0.379	0.117	0.137	0.495	0.045	0.063
Mean in control group	3.713	3.713	1.378	1.378	27.500	0.037	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	3,030	3,030	3,030	3,030	3,030	3,030	3,838	3,838
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	-0.059	-0.058	0.018	0.015
	(0.116)	(0.118)	(0.182)	(0.179)
Strata fixed effects	Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes	Yes	Yes
Baseline control		Yes		Yes
Observations	76	76	75	75
R-squared	0.743	0.744	0.668	0.672
Mean in control group			3.500	3.500

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

	Overall effort[2]		Excessive workload	
	(1)	(2)	(3)	(4)
Treatment	0.033	0.042	-0.206	-0.207
	(0.277)	(0.292)	(0.094)**	(0.093)**
Strata fixed effects	Yes	Yes	Yes	Yes
Health worker controls	Yes	Yes	Yes	Yes
Baseline control		Yes		Yes
Observations	76	76	76	76
R-squared	0.502	0.516	0.602	0.603
Mean in control group	6.303	6.303	0.368	0.368

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	-385.629	0.068	0.098	0.012	0.015
	(193.436)*	-0.125	-0.125	-0.093	-0.098
City fixed effects	Yes	Yes	Yes	Yes	Yes
Health worker controls[2]	Yes	Yes	Yes	Yes	Yes
Baseline control			Yes		Yes
Observations	947	75	75	75	75
R-squared	0.458	0.466	0.484	0.281	0.289
Mean in control group	5,770			0.816	0.816

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	0.006	-0.031
	(0.069)	(0.087)
Observations	85	80
R-squared	0.216	0.424
Mean in Control Group	0.25	0.25
Strata fixed effects	Yes	Yes
Health worker controls		Yes

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						
	Control group		Treatment group		*P-value* Treatment = Control	Number of obs.
	Mean	SD	Mean	SD		
	(1)	(2)	(3)	(4)	(5)	(6)
Male	1	0	0.7	0.483	0.229	21
Age	29.545	11.414	30.5	8.29	0.798	21
General caste	0.273	0.467	0.4	0.516	0.634	21
Hindu	0.727	0.467	1	0	0.026	21
Highest education level achieved						
Other diploma/non-formal education	0	0	0	0		21
Class 12 and below	0.636	0.505	0.7	0.483	0.766	21
Tertiary	0.273	0.467	0.3	0.483	0.896	21
Work experience						
Any previous work experience	0.727	0.467	0.7	0.483	0.917	21
Number of years of work experience	8.8	5.35	10.2	4.341	0.5	20
Any previous experience in the social/NGO sector	0	0	0	0		20
Lives in one of the areas covered by the centers	0.5	0.527	0.5	0.527	1	20
Assets						
Has electricty	1	0	0.9	0.316	0.353	20
Has tap water	0.9	0.316	0.7	0.483	0.34	20
Rents an apartment or house to a third party	0.091	0.302	0	0	0.362	19
Owns land	0.727	0.467	0.667	0.5	0.803	20
Exposure to technology						
Knows how to use a computer	0.727	0.467	0.6	0.516	0.515	21
Knows how to use the internet	0.7	0.483	0.6	0.516	0.636	20
Has an email account	0.545	0.522	0.3	0.483	0.27	21
Has a social networking account	0.636	0.505	0.3	0.483	0.081	21
Baseline number of detections per month per center[1]						
Baseline number of defaults per month per center						
Months spent in the experiment	117.636	93.643	112.2	109.728	0.91	21

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	-0.016	-1.411	0.002	-0.009	0.001	0.041	-0.014	-0.022	0.031	-0.024	-0.007
	(0.019)	(0.791)*	(0.010)	(0.022)	(0.024)	(0.029)	(0.014)	(0.030)	(0.034)	(0.035)	(0.006)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,605	2,604	2,609	2,609	2,609	2,609	2,609	2,609	2,601	2,601	2,601
R squared	0.022	0.023	0.019	0.066	0.063	0.038	0.116	0.126	0.080	0.085	0.042
Mean in control group	0.586	34.432	0.048	0.182	0.356	0.232	0.078	0.104	0.832	0.147	0.021

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	-0.019	0.005	0.013	-0.034	0.003	0.035	-0.019	-0.018
	(0.020)	(0.011)	(0.021)	(0.017)*	(0.007)	(0.026)	(0.024)	(0.013)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,609	2,609	2,609	2,610	2,028	2,028	2,028	2,028
R squared	0.022	0.048	0.029	0.028	0.022	0.024	0.026	0.018
Mean in control group	0.303	0.042	0.654	0.228	0.021	0.481	0.434	0.063

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	-0.126	0.002	-0.020	-0.030	0.055	-0.010
	(0.097)	(0.019)	(0.015)	(0.023)	(0.024)**	(0.022)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,600	2,300	2,595	2,590	2,584	2,600
R squared	0.023	0.019	0.033	0.036	0.023	0.102
Mean in control group	5.522	0.706	0.269	0.332	0.402	0.176

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.