Crowd-sourcing government accountability: Experimental evidence from Pakistan

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Note: This policy brief reports on an ongoing study. Results are preliminary and may undergo change.

Background

In the last ten years, there has been a rapid increase in the penetration of Information and Communications Technologies (ICT) across geographic and socioeconomic boundaries. In Pakistan, the rural poor, a segment of society historically only weakly linked to communication networks, now boast almost universal access to cellular phones. This proliferation creates opportunities to leverage information that were unthinkable a decade ago, making possible programs that would have been hitherto unfeasible. The current study is an attempt to test the feasibility and effectiveness of one such program.

A fundamental problem faced in Punjab, Pakistan and across the underdeveloped world, is that the actions of those that need to be held to account are too costly to observe and monitor. An early attempt to leverage ICTs in this realm was the Citizen Feedback Monitoring Program (CFMP). CFMP requires all government officials from participating offices to collect contact information from citizen-clients, and transmit this information to a centralized calling centre. The centre texts or calls these citizens soon after, and gets feedback on the government officials' performance. The calls ask objective questions such as whether the officials demanded graft, and subjective ones such as the client's level of satisfaction with the service. The information collected is then shared with senior government officials as well as the mid-tier officials directly responsible for the office. The program's emphasis is the use of this information for corrective actions for performance improvement as opposed to individual grievance redressal.

Intervention

In the current project, we applied the basic structure of the CFMP to the Livestock and Dairy Development Department (LDDD) in Punjab, Pakistan, and then added a significant novel development to that design. A major service that LDDD provides citizens is publicly subsidized Artificial Insemination (AI) of cows and buffalos. AI can both increase the success rate of attempts to impregnate an animal, and provide a convenient way to cross-breed livestock varieties to select for favourable animal traits.

In our pilot, conducted in Sahiwal District, Punjab with the district's 77 AI Technicians (AITs), we provided Android based phones to these staff, equipped with a pre-installed Open Data Kit (ODK) based app. This app allowed AITs to collect basic and contact information for the farmers they served. It then transmitted this data back to a central calling centre we commissioned.

Our first, and minor, departure from CFMP as applied elsewhere was to add a second call for each citizen contacted, delayed by two months. While the first call simply verified that the service had been provided, and the price charged, the second call asked the simple question: 'Did your animal get pregnant?' These questions are crucial, because although the government currently maintains an unverifiable paper trail of monthly service provision, it can neither verify the veracity of these reports, nor more importantly, verify quality. AI is a service that can fail at many different steps due to the AIT's actions, but also has a random failure component, so an isolated farmer reporting failure for one insemination attempt is not actionable information. By aggregating success or failure reports across time for each AIT, we can grade them on quality.

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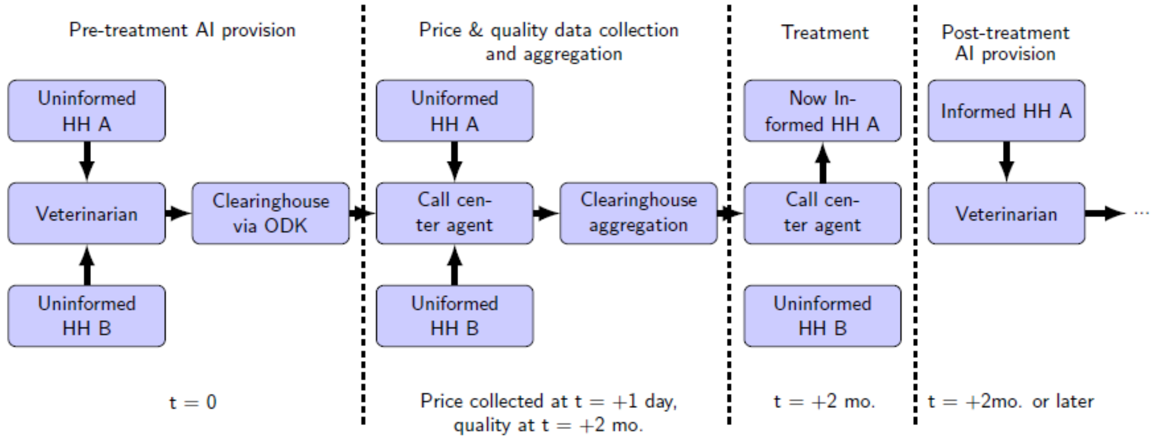

Notes: Arrows indicate the flow of information. The collection of quality data and treatment occur during the same follow-up phonecall two months after service provision.

Figure 1: System Flowchart

Our second, and more substantial extension of CFMP was to make the data public-facing, and leverage GPS data to localize information reports for the public. At the time of the second call, farmers were provided quality rankings, price information and the contact information of the top 3 AITs in their area, separately for cow and buffalo insemination. They were also provided the opportunity to request these details for other AITs. This extension was useful because it directly empowered the recipients of the service to choose who served them.[4]

AITs started entering data into our system in November, 2013; farmers started receiving calls in January and treatment (information provision) calls began in October of 2014. The system was shut down at the end of June, 2015.

Data Collection and Experiment Design

Each farmer utilizing our system received follow-up calls to verify provision and check for insemination success. We randomly assigned some farmers to receive the information on AIT quality, price and contact described above. This was provided in an additional five minutes added to the second call made by the system.

We have two sources of data: the administrative data generated by our system, and data gathered in independent household surveys. For the latter, we conducted a baseline survey of 90 out of approximately 500 villages in Sahiwal district in September 2013. In each village, we selected[5] 10 households to respond, conditional on the household having access to a cell phone and owning 2 or more livestock. An endline was conducted in June 2015, immediately prior to the system being shut down.

Results

First, a major concern within CFMP-type projects is whether the information being provided by officials is accurate, since they may have incentives to hide or fudge the contact information of citizen-clients to avoid accountability[6]. In our scenario, we worried about AITs providing data at differential rates to the system when reporting for treatment versus control farmers. Our data is highly reassuring in this regard: in 730 visits to 440 unique farmers across Sahiwal, there was no significant difference in AIT data reporting across treatment and control.

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[4] In our context, but not across other CFMP applications, the service provided could be procured elsewhere, and had no significant externalities, positive or negative. We note in passing that this extension is not appropriate across all contexts in which CFMP may be applied.

[5] Using the EPI cluster sampling method

[6] Early versions of CFMP suffered from invalid numbers (nonsensical numerical strings) being returned by officials instead of citizens' numbers, and from officials returning duplicate numbers (usually providing their own valid phone numbers instead of citizens'). These problems were addressed over time as CFMP developed in Punjab.

	Treatment	Control	Difference	P-value
Farmer reported AI & vet submitted data to call center (=1)	0.299	0.276	0.023	0.758
	[0.459]	[0.448]	(0.044)	.
Farmer reported receiving a call verifying AI service (=1)	0.287	0.240	0.047	0.566
	[0.449]	[0.422]	(0.041)	.

Notes: Standard deviations reported in brackets. Standard errors reported in parentheses. Treatment and control means and differences are unconditional. P-values reported are from OLS regressions with randomization strata fixed effects and standard errors clustered at the village-cluster level. The sample consists of 730 farmer-visit-level observations from 440 unique farmers across 83 village-clusters from our endline survey. Some regressions have fewer observations due to missing data. "Farmer reported AI and veterinarian submitted data to call center" is a dummy equal to one if a government AI service provision reported in our endline survey was subsequently submitted to the clearinghouse by the veterinarian that performed the service. This is done by verifying survey data with clearinghouse data directly.

Figure 2: Validating Data Provision by AITs

Second, there is evidence that providing farmers evidence of AIT quality significantly increases their use of publicly-provided AI in the future: farmers provided this information are 33 percent more likely to return to a government AIT than their peers without the information.

Finally, farmers provided the information have a 27 percentage point higher AI success rate. Our data suggests that this increase in success rate is not driven by farmers choosing higher quality AITs. Instead, it seems that the higher success rate is driven by AITs exerting greater effort when providing service to informed clients. This greater effort does not translate into any effects, positive or negative, for uninformed clients.

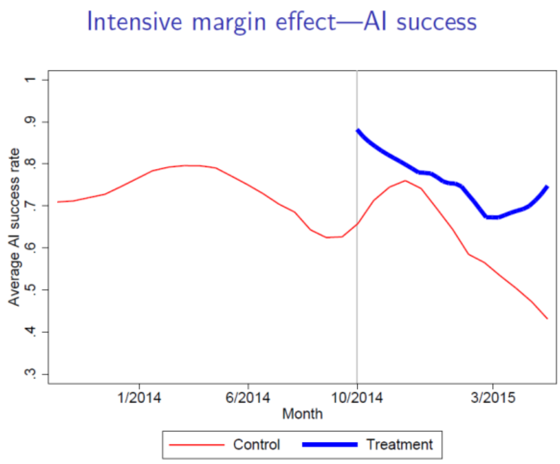

Figure 3: AI success rates for control and treatment groups

Conclusion

Leveraging the penetration of ICT in rural Punjab, this project demonstrates the viability of setting up an information clearinghouse to aggregate quality reviews for government officials providing private goods to citizen-clients. Farmers provided this information saw an increase of income per AI of half a month's expected income. These benefits far exceeded the cost of implementing the system. That this system utilized AIT-supplied information is reassuring because many nascent schemes use self-reported data for auditing purposes. At least in our context, the fears of data fudging seem to have been unfounded.

There are many directions future work in this area may explore. First, there needs to be a better understanding of how to elicit the most accurate and voluminous feedback from citizens, when there is no direct private incentive to do so. Second, the long-term impact of quality information provision needs to be understood, since government-suppliers are likely to adapt their quality and provision strategies as a response to such a system. Finally, the extension of such quality information to the fully private domain needs to be explored.