What you get is what you (can) see: Publicly Observable Generosity and Effort of Healthcare Providers

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Abstract

Healthcare in many parts of the developing world is characterized by low quality of care. We use data from rural Bihar, India, to explore the relationship between healthcare providers' publicly observable donations and quality of care delivered. We analyze data on providers' clinical effort both when they are and are not aware that they are being observed, combined with data from a lab-in-field study that induced publicly observable donations. Providers who donate out of pocket also exert high levels of effort with patients when they know that they are being observed but not when they do not know.

Key Words: Performance, Quality, Health Care, Generosity, Audit, Lab in Field

JEL Classifications: D64, I10, J20

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1 Introduction

A growing literature on the economics of health and development documents the low quality of healthcare received by households in developing countries (National Academies of Sciences and Medicine, 2018; Das et al., 2008). Low quality of care continues to be a major contributor to the global burden of disease either indirectly, when patients do not recover from treatable illnesses in a timely manner due to inappropriate or inadequate care, or directly when poor quality care leads to worse health (such as medical errors and iatrogenic deaths) (National Academies of Sciences and Medicine, 2018; Das et al., 2018).[1]

One problem with quality of health care, especially in rural developing country settings, is that clinical aspects of quality can be unobservable or unknown to patients at the time of care due to information asymmetry (Arrow, 1963; Das and Hammer, 2014). Patients might be able to infer quality ex-post based on their recovery from ill health after receiving care, but such learning is difficult in primary care settings where many illnesses (such as viral infections) might be self limiting or if other health behaviors are equally important determinants of recovery in addition to appropriate pharmacological treatment. Under such settings, providers might have fewer incentives to exert effort to provide care that is clinically appropriate but not observable and instead divert effort to tasks that are observable to the patient. In developed country settings, patients value communication with their healthcare provider, are less likely to sue

[1] Quality of care is an especially daunting challenge in settings like Bihar, India, where this study was conducted. Bihar is one the poorest states in India, with health and development indicators that are among the lowest in the country. According to India's latest NFHS survey data in 2015-16, the under-five mortality rate in the state was 58 per 1000 live births (IIPS, 2017). Healthcare practitioners in the state have low levels of knowledge about how to treat common medical concerns and also perform inadequately when diagnosing and treating patients (Mohanan et al., 2015).

providers who have better bedside manners, and they also report higher satisfaction when prescribed antibiotics that are not strictly necessary (Vick and Scott, 1997; Tamblyn et al., 2007; Martinez et al., 2018).

Providers' performance is driven by a number of factors. Studies that introduce peer observers to induce Hawthorne effects find that the quality of care delivered improves when providers know they are being observed (Leonard and Masatu, 2006, 2010a,b). Similarly, studies of performance incentives find that adequately high-powered incentives can induce providers to deliver higher quality care and improve health outcomes (Miller and Babiarz, 2014). Furthermore, providers might be driven by reputation even when there are no direct financial returns to quality improvement (Kolstad, 2013). The wide range of factors driving provider behavior also makes it challenging to study this behavior and to develop interventions to deliver higher quality of care, especially in rural areas of the developing world.

In this paper, we study the behavior of rural healthcare providers and the quality of care they provide using a unique combination of datasets from rural Bihar in India. We analyze data on providers' clinical effort both when they are aware and when they are unaware of being monitored (during audit visits by standardized patients), combined with data from a lab-in-field study that induced publicly observable donations. Our analysis shows that providers who donate out-of-pocket to a health-related NGO in publicly observable survey settings also exert higher clinical effort with patients when they know that they are being monitored, but they exert similar amounts of effort with unannounced standardized patients. Thus the patterns of care reported in the literature such as overprescription of unnecessary drugs by providers in settings such as ours (rural areas with informal sector providers delivering primary care) could be motivated by providers seeking to bolster their overall reputations. It is important to consider this motivation when designing policies to improve quality of healthcare provision in developing country settings. Furthermore, similar to the empirical results on Hawthorne effects in studies of provider quality, our results suggest that relying on methods that are observable to the provider could yield upwardly biased estimates especially among providers who are most concerned about reputation.

2 Context

The question of how to motivate high quality of care is particularly important in developing country settings, as households in such settings face generally low quality of healthcare. Households in India have access to many healthcare options within reasonable distances of their homes, and healthcare makes up a significant proportion of the regular household budget (Banerjee et al., 2004; Das et al., 2008). However, households mostly have access to *low-quality* healthcare, across the socioeconomic spectrum (Das and Mohpal, 2016). Very few healthcare providers serving rural and low-income populations in India are actually qualified to provide medical care. In our sample of private healthcare providers in rural Bihar, only about four percent of providers had an MBBS, which is comparable to other rural contexts in northern India (Das et al., 2016).[2] Furthermore, there are high rates of absenteeism - providers often are not physically present at the times when the facility is supposedly open (Banerjee et al.,

[2]MBBS is the basic formal medical degree for training in allopathic medicine in India; it stands for Bachelor of Medicine, Bachelor of Surgery, and is equivalent to the MD in the US.

2004; Chaudhury et al., 2006).

When providers are accessible, the interactions between providers and patients are brief. In our sample, when providers do not know that they are being observed, interactions between the provider and the patient are less than two minutes. This is comparable to estimates for other parts of India (Das et al., 2008). During such brief exchanges, healthcare providers rarely ask the correct questions to be able to accurately diagnose conditions (Das et al., 2008). Given such oversights, providers are unsurprisingly unable to accurately diagnose conditions very common in the area (Das and Hammer, 2004b). Thus, treatment is often incorrect: overprescription of IVs, injections, and antibiotics is commonplace (Banerjee et al., 2004; Das and Hammer, 2004a; Mohanan et al., 2015).

An important component of quality of care is whether healthcare providers exert the optimal level of effort with patients. However, in many healthcare systems, doctors don't have the correct incentives to do so (Miller and Babiarz, 2014). Even when providers know correct procedures, providers (including in the setting of this paper) do not follow these procedures with their patients, exhibiting a "know-do" gap (Das et al., 2015; Mohanan et al., 2015).

A growing literature seeks to understand how to incentivize healthcare providers to provide optimal quality of care (Miller and Babiarz, 2014). This literature has studied both the importance of agency over one's own work and financial incentives, finding mixed results. In developed countries, doctors overprescribe treatments, procedures, and brand-name drugs when it is profitable, but providing physician report cards better incentivizes improvement in care than financial incentives (Feldstein, 1973; McGuire, 2000; Johnson, 2014; Johnson and

Rehavi, 2016; Crea et al., 2017; Kolstad, 2013). In India, there is a quality premium in prices - private providers who provide palliative treatments, *unnecessary* treatments, and have higher qualifications are able to charge patients higher prices; the same providers exert more effort with patients in their private clinics than their public facilities (Das et al., 2016). Providers' effort improves with monitoring in Tanzania; a subset of providers in this setting consistently maintain high levels of communication with patients; these providers are just as likely to work in centralized or decentralized sectors (i.e. public versus private) - facing very different incentives for providing high quality of care (Leonard and Masatu, 2010a, 2006). Provision of healthcare can include a pro-social component; pro-social motivation can be thought of as a requirement to ensure that healthcare providers exert the optimal level of care (Brock et al., 2015). For example, pro-socially motivated nurses who demonstrate higher generosity to patients in dictator games are more likely to choose rural jobs (Lagarde and Blaauw, 2014).

This paper seeks to understand the motivations of healthcare providers by exploring the relationship between a publicly observable donation by providers and quality of and effort in healthcare provision. To answer this question, we use a unique dataset of healthcare providers in rural Bihar, India. We use a lab-in-field elicitation of a donation from the healthcare provider to a locally active NGO which we interpret as a publicly observable indicator of generosity.[3] The results from the donation elicitation are combined with measures of healthcare provider effort, and treatment/diagnosis accuracy. We show that healthcare providers in rural Bihar, India who donate out-of-pocket in this publicly observable elicitation are likely to improve performance

[3]This generosity could be related to altruism, intrinsic motivation, or other forms of pro-social motivation, but we do not seek to identify those separate effects (Andreoni, 1990; Ariely et al., 2009).

when monitored. They value being held in high regard by their community, and this desire to be esteemed is correlated with the exertion of more effort with patients.

Crucially, we are able to measure healthcare provider effort and quality when providers do and do not know that they are being observed. If healthcare providers in this setting are motivated at least in part by reputation, then we should see that those who donate outsize amounts to the local NGO should exert significantly more effort with patients than their peers when they *know* that they are being observed, but not necessarily so when they *do not know* that they are being observed. We do find that those providers who donate out-of-pocket to a health-related NGO in the area, a publicly observable indicator of generosity, also exhibit high levels of effort when they know that they are being observed. However, when these providers do not know that their patient care is being observed, their observable generosity is largely uncorrelated with provider effort.

3 Data

Our analysis relies on four sources of data that were collected in 2014-2015 as part of a study of private healthcare providers and social franchising models of healthcare delivery in rural Bihar, India.[4] We rely on (a) surveys of providers that include information on provider characteristics, demographics, qualifications and infrastructure, and knowledge of providers as reported on case vignette interviews; (b) direct observation studies where enumerators observed providers

[4]The Bihar Evaluation of Social Franchising and Telemedicine project, funded by the Bill and Melinda Gates Foundation, studied provider quality and the effect of introduction of telemedicine and social franchising based business models to deliver care in rural areas of Bihar. Mohanan et al. (2016a).

for an entire business day and recorded data on care provided; (c) data from standardized patients, where highly trained enumerators present standardized cases in audit study visits to measure provider performance; and (d) data from a lab-in-field elicitation of donations to a local charity as a publicly observable indicator of generosity.

The sample of providers in our study is representative of providers in rural areas of Bihar, where few providers have formal medical degrees and most are informal sector providers. In our sample, about four percent of providers have an MBBS degree, and about 13% have a BAMS degree.[5] Almost all (94%) of providers practice allopathy (western medicine) even if they have no formal training.[6] These providers, almost all of whom are in private practice, reported that they had 17 years of experience and see 14 patients per day on average, ranging from one patient to 63 patients across providers. The providers charge on average 75 Indian Rupees (INR) as a consulting fee, earning an average of 525 INR per day.[7]

The sample of providers in our analysis comes from the telemedicine evaluation study in Bihar that was designed to estimate the quality of care that households in the study area receive when they utilize healthcare for common conditions. Thus, rather than sampling providers randomly within the universe of providers in the study area, the study enrolled providers who were reported to be the most commonly visited providers by a large representative set of households in the study cluster. These clusters are distinct from administrative boundaries such as villages, blocks, or districts. Given the objective of the original study to evaluate the impact of telemedicine and social franchising business models, the study cluster areas were defined as

[5] BAMS (Bachelors of Ayurveda, Medicine, and Surgery) is a degree awarded after training in Ayurveda - the Indian system of medicine.

[6] Alternatives to western medicine include Ayurveda and homeopathy.

[7] These averages come from the provider observation data, rather than providers' self-reports.

a central village which had access to high speed internet connectivity and was located on or near major road networks, with surrounding villages that were sufficiently geographically close. Study clusters typically covered a population of about 10,000 households. Within each of these clusters, a random sample of 64 households were asked to list all healthcare providers that they visited in the last six months. The five most frequently named providers in each cluster were then selected for follow-up data collection. Our final data from 80 study clusters where the project collected data on provider performance includes information on 377 providers.[8]

The provider quality surveys were conducted between June and December 2014. The providers were first approached for survey interviews, where information regarding their age, educational background, experience, and facilities, were collected. At this point, they also consented to receiving follow-up visits from enumerators to conduct vignettes and provider observations, and visits from standardized patients.

First, for provider observation, enumerators observed the providers' practice on an unscheduled visit - recording the patient caseload, demographics of patients, and observing provider-patient interactions to ascertain the amount of time spent with patients, types of questions asked, examinations conducted, and types of treatment provided or prescribed. This measurement method yields the type and level of effort that providers exert when they are aware of being observed. Second, the research team conducted an audit study using unannounced standardized patients (SP), presenting specific tailored cases of a father whose child is presenting symptoms of diarrhea or pneumonia, to measure quality of treatment when the provider does

[8]For further information on study clusters and sampling refer to Mohanan et al. (2015, 2016a,b)

not know they are being observed.[9] Importantly, by standardizing and controlling the cases that the providers see in the SP methodology, the researcher is able to measure whether the provider accurately diagnosed and treated the patient.

One constraint with the SP method is that SPs can only be deployed in clinic locations with a sufficiently large patient volume such that new patients would not be conspicuous by their presence and the provider might suspect that they are part of the research team. As a result, the sample size for SP based measures of provider effort is lower than for the provider observation data. Within the set of providers where the SP methodology could be carried out, providers were randomly selected to receive either the diarrhea case or the pneumonia case. This sample is similar to the full sample across the main descriptive variables[10].

In a separate visit which was conducted in June 2015 (a year after the provider surveys), enumerators conducted a lab-in-field donation elicitation with the providers.[11] The lab-in-field elicitation was conducted in the consulting room of the health care provider's facility - most providers' facilities were basic with either just one room that had no privacy or if the facility had a separate examination room, the surveys and interviews were conducted in the main consulting area which is public. While the elicitation was originally intended to be private where provider donations would not be observable, in practice, it was often observed by patients

[9] In rural Bihar, it is not uncommon for a parent, typically a father since women traditionally stay within the home, to seek care on behalf of a child who is unwell at home. The SP case of a parent of an unwell child has been developed and implemented successfully in a number of previous studies and settings in Bihar and elsewhere (Das et al., 2015; Mohanan et al., 2015; Sylvia et al., 2015).

[10] See Appendix

[11] The follow up visits were conducted as part of data collection for the evaluation of the social franchising program. The donation elicitation was part of an effort to collect information on factors that could explain providers' decision to adopt the telemedicine franchise model. This first stage of a series of tasks and games was developed and implemented by Manoj Mohanan, Marcos Vera Hernandez and Pau Olivella as part of the telemedicine evaluation project.

or local passers-by. Like most surveys in rural India, the arrival of enumerators bearing a survey instrument invariably attracted onlookers. Consequently, social norms of survey interviews being conducted publicly resulted in the donation elicitation being implemented with community members observing the process.

The elicitation was structured in the following way: the enumerator introduced the task after completion of an in-person survey about adoption of the telemedicine / franchising model when it was promoted in their area during the preceding years. As compensation for their time for responding to the survey, providers were given 100 INR in denominations of 10 INR at the beginning of the survey.[12] This amount is under 20% of what an average provider would earn in a day's work. The enumerator then offered the providers an opportunity to make a charitable donation to Smile Train - an NGO very active in the region[13]. Smile Train provides free reconstructive surgery to children born with cleft lip. Since the NGO is active locally, the providers were already very aware of this organization and its work. A key reason for choosing Smile Train as the beneficiary was that a charity providing free surgical care to children would be particularly salient to healthcare providers. The enumerator then reminded the provider of the 100 INR given to them and gave the provider an envelope that they could place any cash (or none) if they wished to donate to Smile Train. Although enumerators were trained to specify that the amount is private information and they should place any amount (or none) privately and return a sealed envelope to the enumerator, in practice most providers made the donation publicly often declaring the amount of money donated. The enumerator then

[12] 100 INR was about $1.57 in 2015.
[13] https://www.smiletrainindia.org/

collected the envelope and the donated amounts of money were transferred to Smile Train. The mean amount donated to Smile Train is 105 INR - meaning that the average provider in the sample donated the entire amount that they received as compensation for survey participation, approximately 20% of daily income, to Smile Train.

4 Empirical Strategy

The objective of our analysis is to explore the relationship between healthcare provider' public generosity as measured in the lab-in-field donation and their effort in healthcare, specifically to test whether providers who donate more in the publicly observable elicitation setting exerted different levels of care when they were aware of being observed compared to when they were unaware of being observed. We first explore patterns in donations made by providers in the lab-in-field elicitation, and then correlate observed donations to measures of provider performance. We rely on an OLS model in our main analyses. In the provider observation data (measuring effort, when providers know that they are being observed), we observe multiple provider-patient interactions for each provider. Thus, this model takes the provider-patient interaction as the unit of observation. Equation 1 is used for a set of outcome variables measured at the provider-patient interaction level: including length of visit in minutes, whether a physical examination was conducted, whether immediate treatment was given, etc.

$$y_{ijd} = \beta_0 + \beta_1\gamma_{id} + \beta_2\zeta_{id} + \Gamma X_{id} + \Lambda K_{ijd} + \delta_d + \varepsilon_{ijd} \quad (1)$$

Here, j refers to the particular patient for provider i, while d denotes district. The variable γ_{id} refers to the provider's result from the generosity elicitation - this indicator variable is equal to 1 if the provider donated strictly greater than 100 INR to Smile Train. We use 100 INR as the cutoff as it indicates that the provider donated money out-of-pocket, beyond the compensation they received for participating in the survey. X_{id} refers to a vector of covariates capturing provider characteristics: age, age squared, years of experience, an indicator for MBBS, an indicator for BAMS, an indicator for other educational qualifications, an indicator for practicing allopathy, an indicator for practicing Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), an indicator for being a public provider, an indicator for selling medicines, average fee for the visit, and an infrastructure index. Summary statistics for all covariates are in the appendix. We also include a vector of covariates K_{ijd} denoting the age and gender of the patient j. The regression includes a district fixed effect (δ_d) to account for any differences in healthcare markets across districts. Finally, this model includes a covariate for the number of patients that the provider saw on the observation day, denoted ζ_{id}. Standard errors are clustered at the provider level, to account for within-provider correlation in treatment of individual patients.

The standardized patient data (measuring effort, when providers do not know that they are being observed), is defined at the provider level. Thus, we take the provider as the unit of observation for these regressions. Equation 2 is used for a set of outcome variables measuring diagnosis and treatment effort and accuracy, for either the SP diarrhea or SP pneumonia case to which the provider was randomly assigned.

$$y_{ikd} = \beta_0 + \beta_1 \gamma_{id} + \beta_2 \eta_{ikd} + \Gamma X_{id} + \delta_d + \omega_k + \varepsilon_{ikd} \tag{2}$$

Here, i denotes the provider, d denotes the district, and k denotes the enumerator who posed as the SP. The diarrhea and pneumonia cases are pooled into the same regression, and we include a covariate (η_{ikd}) indicating whether the outcome is measured from the diarrhea case. This model includes a SP fixed effect (ω_k) for each of the enumerators who trained and posed as patients, to account for any differences in how specific individuals presented the cases. All standard errors in this model are bootstrapped, to account for small sample size.

Finally, we include an OLS model of the relationship between the price of the visit (in INR), and characteristics of the provider and the visit, estimated at the provider-patient visit level. These regressions are estimated on two samples: the provider observation sample (where the provider knows that they are being observed) and the standardized patient sample (where the provider does not know that they are being observed). The specification is as follows:

$$\rho_{ijd} = \omega_0 + \Gamma X_{id} + \Lambda W_{ijd} + \delta_d + \varepsilon_{ijd} \tag{3}$$

Here, i refers to the provider, j refers to the provider-patient interaction, and d refers to district. The outcome of interest is total charge to the patient, in INR. X_{id} is a vector of provider/facility level characteristics. In both samples, this includes whether the provider has an MBBS, provider's age, and whether the facility is open at night. W_{ijd} is a vector of provider-patient interaction level characteristics. In the provider observation sample, this includes the length of the visit in minutes, whether an injection was given, whether an IV was given, whether written documents were provided, whether instructions were given, whether a physical examination was conducted, whether the provider gave treatment during the visit, the number of medicines dispensed, and whether the patient was a child and/or female. In the SP data, this vector includes the length of the visit in minutes, the number of medicines dispensed, whether any treatment was provided during the visit, whether any explanation was given, and whether the treatment was correct. In both samples, fixed effects for district are included, and standard errors are bootstrapped. In the standardized patient sample, SP fixed effects are also included.

5 Results

Figure 1 shows the distribution of providers' donations to Smile Train in the donation elicitation. As described earlier, the providers were given 100 INR in cash as compensation for survey participation and later asked if/how much they would like to donate to Smile Train in the generosity elicitation. The median response was 100 INR and 24% of providers gave strictly more than 100 INR to Smile Train, meaning that they gave additional money out-of-pocket. The largest donation was 600 INR - which is more than the average provider earns in a single day. The large relative sizes of these contributions raise the question of whether these donations are purely altruistic or whether these donations responded to other factors. Although the elicitation was designed to be implemented as a private donation, in practice there were regularly onlookers observing the survey interactions. The potential for biased responses due to social desirability and bystander effects has long been a concern in survey research on sensitive topics (Krumpal, 2013; Nederhof, 1984). Field enumerators noted that providers were behaving in this way to demonstrate their generosity to bystanders. Smile Train is very active in the area and providers were familiar with the NGO and its work. All providers could have readily donated money to Smile Train at any other point in time without being prompted by the enumerator; though there is no such evidence. [14] Thus, the donations made in this elicitation were likely motivated at least in part to bolster the provider's reputation of generosity and caring for the community.

[14] The director of communications and business development for Smile Train India confirmed to us via personal communication that no healthcare providers from rural Bihar have donated to their organization, barring the donation made as part of the study.

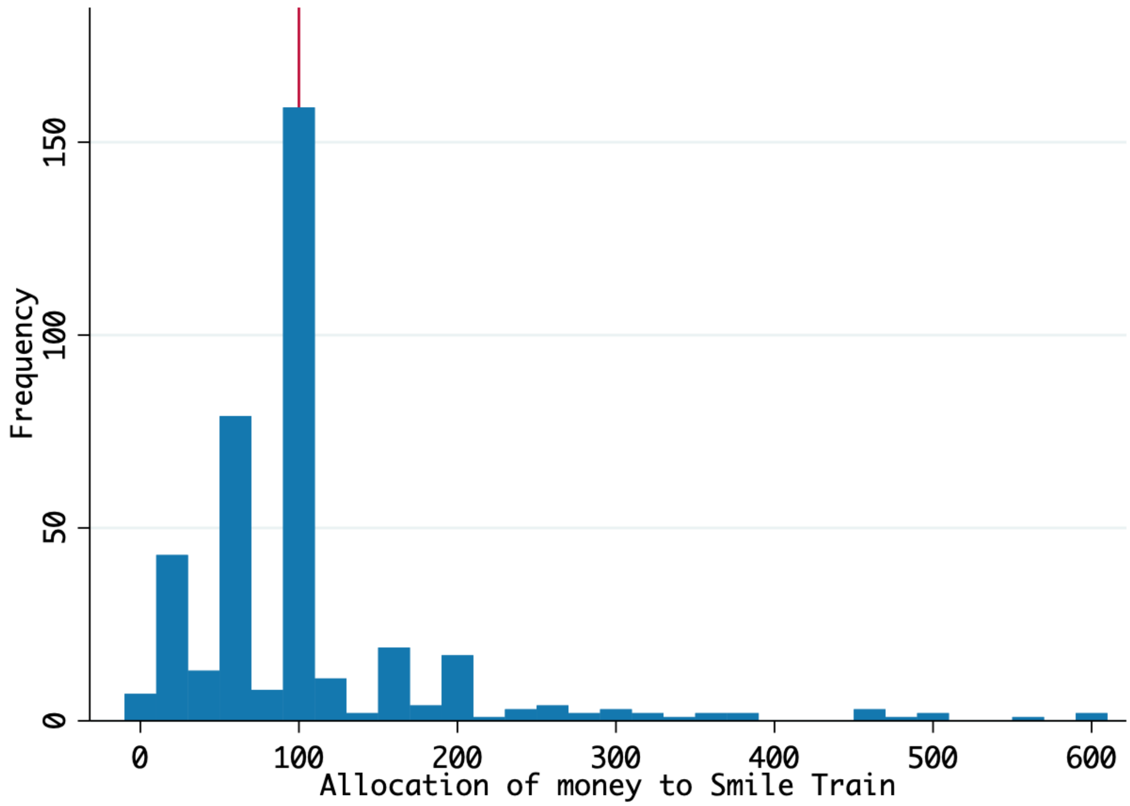

Figure 1: Histogram of Donations to Smile Train

Notes: Vertical line indicates 100 INR.

We construct an indicator variable γ_{id} - for whether the provider gave a donation strictly above 100 INR - as the key explanatory variable of interest for our analysis. A donation of 100 INR in a rural setting like Bihar is notably large, and in the context of the lab-in-field elicitation, conspicuous. We start by analyzing data from provider observations, where providers are aware that they were being observed - a self-declared enumerator arrived on an unscheduled visit on a randomly selected day to observe all of the provider's interactions with patients. The outcomes in Table 1 are at the patient-provider interaction level, with each column showing results from regressions that estimate Specification 1.

Table 1: Provider Observation Regressions

VARIABLES	(1) Physical examination	(2) Written documents	(3) Gave instructions	(4) Immediate treatment	(5) Minutes	(6) Number of medicines	(7) Number of history questions
Donation over 100 INR	0.00592	0.0733*	0.0109	0.0271	0.559	0.188**	0.231*
	(0.0323)	(0.0413)	(0.0396)	(0.0359)	(0.352)	(0.0919)	(0.122)
Observations	2,673	2,673	2,673	2,673	2,673	2,673	2,673
R^2	0.128	0.336	0.059	0.129	0.047	0.071	0.080
Mean	.566	.337	.68	.288	7.648	3.582	3.011

Notes: Estimates obtained through OLS. Robust standard errors, clustered at the provider level, are reported in parentheses. *, **, and *** denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects, and the following covariates: age, age squared, years of experience, indicator for MBBS, indicator for BAMS, indicator for other educational qualifications, indicator for practicing allopathy, indicator for practicing Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), indicator for public provider, indicator that the provider sells medicines, average fee for the visit, and infrastructure index. All dependent variables are measured through provider observations conducted between August and October of 2014. The dependent variables in order presented in the table are an indicator for physical examination, indicator that the patient was given written documents, indicator that the provider gave the patient instructions for home care, indicator that the provider treated the patient immediately at the visit, the duration of the visit in minutes, the number of medicines prescribed, and the number of medical history questions the provider asked the patient. The duration of the visit includes time that the patient might have been waiting to see the provider.

The results show that providers who donated out-of-pocket were statistically significantly more likely to provide written documents, ask more questions about history and prescribe more medicines. The coefficients in these regressions suggest that providers donating money out-of-pocket (in excess of the 100 INR they were given as compensation for the survey) were about 20% more likely to give written documents to patients, ask about 8% more history questions and prescribe about 5% more medicines, relative to the mean levels in the sample. Providers who donated out-of-pocket also spent about 0.56 minutes more with each patient - this estimate is nearly significant at the 10% level (p-value of 0.11). The coefficients on other measures - conducting physical exams, giving instructions on treatment, and providing treatment immediately are all positive, but are not statistically significant at conventional levels. Asking more history questions, providing written documentation, and prescribing more medications could be interpreted as exerting more effort, but these are also conspicuous types of effort that are easily observable to the enumerator in provider observation settings. As a result, it is difficult to disentangle better care from providers trying to exert effort on visible measures even if they are not necessarily productive - similar to the multi-tasking concern in contract theory. Without knowing the true condition of each of the patients, we cannot infer whether the treatment provided was the correct one, or whether provider effort was diverted to visible inputs that do not necessarily improve clinical quality of care.

The standardized patients (SP) method enables us to address both of these concerns. The cases are predefined with carefully scripted presentation of symptoms so the underlying illness and its appropriate treatment is known to researchers. Furthermore, the SPs are rigorously trained to be indistinguishable from normal patients in the area to ensure that providers are unaware that their actions are being observed by study enumerators (Das et al., 2012). For our analysis of data from SP visits, we pool the diarrhea and pneumonia cases together to focus first on correct diagnosis and treatment in Table 2.[15] Panel A presents results for diagnosis: including whether the correct diagnosis was given, whether the provider asked to see the child, and the number of history, cause, severity, and essential questions that were asked. Panel B presents results for treatment: whether the correct treatment was given, whether oral rehydration salts were prescribed, whether counseling was given about food, and whether any explanation was given for the treatment. None of the specifications for either diagnosis or treatment are significant, and all are low in magnitude.[16] Panel C presents overall measures of provider performance. The Global Assessment Scale is an indicator of whether the SP felt that the provider gave him good medical care. On this purely subjective measure, providers who donated out-of-pocket outperformed their peers. Taken together, we see that when providers do not know that they are being observed, there are no large differences in effort between providers who do and do not donate out-of-pocket (more than the 100 INR originally given to them). The one exception is the subjective measurement - where SP enumerators felt that they received better overall care from the providers who donated out-of-pocket, relative to those who did not. This is particularly striking given that the SP data were collected nearly a year

[15]The correct treatment for diarrhea was to only give ORS, while the correct treatment for pneumonia was antibiotics. Not a single provider gave the correct treatment for diarrhea (all overtreated). A higher rate correctly treated pneumonia, but this likely reflects a high rate of false positives due to the overprescription of antibiotics common in this context. We also estimated the same regressions on separate samples for diarrhea cases and pneumonia cases (dropping the indicator for being a diarrhea case), and do not find significant results. Qualitatively the results are similar to the pooled results, although with half of the sample size.

[16]Results are robust to whether or not we classify referring the patient to a different provider as correct treatment. This is due in part to a very low rate of referrals in the SP cases.

prior to the lab-in-field elicitation, suggesting potential differences in personalities or behavior of providers who donate more that are not picked up in measures of clinical care.

Table 2: Standardized Patient Regressions

Panel A: Diagnosis						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Correct diag	Asked to see child	Num history Qs	Num cause Qs	Num severity Qs	Num essential Qs
Donation over 100 INR	0.0181	-0.0111	0.103	-0.0287	0.0540	0.0253
	(0.0338)	(0.0677)	(0.236)	(0.138)	(0.0875)	(0.147)
Diarrhea	-0.0455	-0.243	-0.640	0.0307	0.554***	0.585
	(0.0630)	(0.149)	(0.515)	(0.214)	(0.191)	(0.425)
Observations	318	318	318	318	318	318
R^2	0.152	0.214	0.270	0.225	0.220	0.185
Mean	.069	.261	3.16	1.305	.248	1.553
Panel B: Treatment						
	(1)	(2)	(3)	(4)		
VARIABLES	Correct treat	ORS	Counsellng about food	Explanation		
Donation over 100 INR	0.0465	0.0534	0.0169	0.00939		
	(0.0374)	(0.0754)	(0.0233)	(0.0305)		
Diarrhea	-0.150***		0.0709	-0.0673*		
	(0.0548)		(0.0513)	(0.0357)		
Observations	318	160	316	318		
R^2	0.226	0.148	0.127	0.270		
Mean	.079	.138	.022	.940		
Panel C: Overall						
	(1)	(2)				
VARIABLES	Global Assessment Scale	Minutes				
Donation over 100 INR	0.0710**	0.0220				
	(0.0358)	(0.0983)				
Diarrhea	-0.222***	0.236				
	(0.0837)	(0.204)				
Observations	316	318				
R^2	0.234	0.291				
Mean	1.874	1.754				

Notes: Estimates obtained through OLS. Bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects, and the following covariates: age, age squared, years of experience, indicator for MBBS, indicator for BAMS, indicator for other educational qualifications, indicator for practicing allopathy, indicator for practicing Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), indicator for public provider, indicator that the provider sells medicines, average fee for the visit, and infrastructure index. All dependent variables are measured through standardized patient visits to the providers between July through September of 2014. The dependent variables in order presented in Panel A are indicators for correct diagnosis and asking to see the child, and the number of questions asked about medical history, cause of illness, severity of symptoms, and those essential for diagnosis. The dependent variables in order presented in Panel B are indicators for correct treatment, prescribing oral rehydration salts, counseling about food, and providing an explanation of treatment. The dependent variables in order presented in Panel C are the global assessment scale and the duration of the visit in minutes.

Our final set of results in Tables 3 and 4 investigate the presence of a quality premium in prices, both when providers know and do not know that they are being observed. We are unable to separate out whether the determinants of price are supply or demand driven. Instead, we examine if there are systematic characteristics of providers, clinics, and visits that are correlated significantly with prices charged. Using data from provider observation (Table 3), we see that providers with an MBBS are able to charge about 75% higher prices, and providers are able to charge about 25% higher for each additional medication that they dispense. However, providing written documentation to patients is associated with about 30% less in total charges, likely because these providers did not give medicines. The results also indicate that providers charge about 50% more if they give the patient an IV. At lower magnitudes, providing verbal instructions, spending an additional minute with the patient, and having a facility that is open at night are also significantly correlated with a higher total charge to the patient. Furthermore, referring the patient to another provider is associated with a 20% reduction in price.[17] Our findings are similar to what was reported in Das et al. (2016) and Wagner et al. (2018); there is a quality premium in prices in such settings, and that this quality premium is more pronounced with easily visible or observable measures of effort. Column 2 includes the indicator for donating more than 100 INR to Smile Train; this dampens the magnitude of the correlation with having an MBBS, and the negative correlation between price and the patient being a child is now negative, but other magnitudes and significances are largely unchanged. The coefficient on donating over 100 INR itself is not significant. While a large donation to Smile Train is correlated with

[17]Donating out-of-pocket did not have a significant relationship with the incidence of referrals in the provider observations data.

more effort on average in the provider observation dataset, where providers were aware that they were being observed, they do not charge higher prices to patients.

Table 3: Price Regressions - Provider Observations

VARIABLES	(1) Price (INR)	(2) Price (INR)
Donation over 100 INR		2.165
		(3.498)
Provider has mbbs	56.53***	44.55***
	(6.397)	(7.419)
Age of provider	0.0590	0.122
	(0.117)	(0.121)
Duration of visit in minutes	1.985***	2.098***
	(0.410)	(0.459)
Injection given	4.731	5.512
	(5.106)	(5.401)
IV given	38.40*	39.96*
	(19.93)	(20.80)
Written documents	-20.79***	-22.89***
	(3.392)	(3.727)
Instructions given	8.902***	8.514***
	(2.830)	(2.980)
Physical examination	8.582***	8.353**
	(3.080)	(3.273)
Immediate treatment	6.341	7.850*
	(4.112)	(4.361)
Number of medicines	20.12***	20.53***
	(1.676)	(1.780)
Referred to another provider	-14.78*	-14.50*
	(7.749)	(8.385)
Facility open at night	7.154**	9.693***
	(2.983)	(3.170)
Public facility	-0.376	16.70
	(20.74)	(29.47)
Patient is child	-4.606	-7.078**
	(3.007)	(3.216)
Patient is female	3.806	4.066
	(3.264)	(3.482)
Constant	-17.27*	-22.68**
	(9.632)	(10.01)
Observations	2,905	2,673
R^2	0.212	0.214
Mean	73.334	73.334

Notes: Estimates obtained through OLS. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects. The dependent variable, total price charged to the patient in INR, was measured through provider observations conducted between August and October of 2014.

Our analysis of data from standardized patient visits, again pooling the diarrhea and pneumonia cases, shows similar results as seen earlier with provider observations. Table 2 shows that exerting more effort with the standardized patient (as measured by length of the visit and whether the provider gives an explanation of the diagnosis/treatment) is correlated with higher total charges, as is care provided in a public facility. The coefficients for MBBS are imprecisely estimated; which is consistent with the small number of MBBS providers in the SP sample. Including an indicator for donating out-of-pocket in the regression (in column 2) further reduces the positive correlation between having an MBBS degree and prices charged, suggesting that the MBBS providers also donated larger amounts of money. The facility staying open at night is also correlated with slightly lower fees, almost equal in magnitude to the effect of one additional minute of visit time. Taken together, this evidence on the relationship between care provided and prices charged from standardized patient visits suggests that the premium for quality of health care in these rural primary care settings is driven by effort that is easily observable to the patient.

Table 4: Price Regressions - Standardized Patients

VARIABLES	(1) Price (INR)	(2) Price (INR)
Donation over 100 INR		-5.590
		(5.902)
Provider has mbbs	28.49	11.23
	(22.61)	(14.10)
Age of provider	-0.118	-0.0378
	(0.239)	(0.298)
Duration of visit in minutes	8.015***	8.460***
	(2.138)	(3.177)
Number of medicines dispensed	-5.743	0.388
	(8.676)	(9.751)
Explanation given	67.26***	59.69***
	(11.74)	(10.62)
Referred to another provider	-29.84***	-36.32***
	(11.14)	(10.73)
Facility open at night	-9.789	-9.048
	(6.351)	(5.955)
Correct treatment	-4.573	-5.160
	(8.603)	(8.993)
Constant	5.786	5.799
	(13.40)	(17.04)
Observations	379	345
R^2	0.249	0.246
Mean	67.977	67.977

Notes: Estimates obtained through OLS. Bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects and controls for whether the provider is a public provider. The dependent variable, the total price charged to the patient, is measured through standardized patient visits to the providers between July through September of 2014.

6 Conclusion

This paper uses novel data on healthcare quality, provider effort, and a publicly observable lab-in-field donation elicitation to shed light on what motivates the behavior of healthcare providers in a developing country context. We use data on providers' clinical effort, diagnosis and treatment when they are unaware of being monitored during audit visits by standardized patients, and data collected by enumerators sitting in providers' offices to directly monitor them. Our results show that providers who make out-of-pocket donations in a publicly observable lab-in-field elicitation exert more effort than their peers when they know that they are being observed, but do not perform significantly differently from their peers when they do not know that they are being observed.[18] We also document a quality premium in prices in this setting - providers with an MBBS charge drastically higher prices, and providers are able to charge higher prices for effort that is observable to patients - both when providers know and do not know that they are being observed. However, neither correct treatment of patients (from SP data) nor large donations to Smile Train are significantly correlated with higher prices paid by patients.

Understanding the links between motivations for healthcare providers and actual patient outcomes is important for policies that aim to improve quality of care. Our findings suggest that bolstering reputation within their community is a significant motivation for healthcare providers in these settings, and given an opportunity to publicly demonstrate higher level of

[18]We also completed similar analysis for data from provider vignettes, which measure providers' knowledge during survey interviews where enumerators ask providers what care they would provide for specific clinical cases. We do not find differences between providers who do or do not donate out-of-pocket on these knowledge measures. Results are included in the Appendix.

patient care, they could be motivated to improve the care they deliver. These findings also suggest supporting efforts such as quality rating and accreditation that provide patients with signals of quality and performance of healthcare providers. Furthermore, the difference in providers' performance between when they are aware of being observed and when they are not also underscores how information asymmetry in such settings contributes to lower effort than what providers could potentially exert.

Our study also draws attention to potential problems with data on provider behavior that is collected in field settings, where bystander effects can be substantial in influencing responses. Previous research has documented the presence of Hawthorne effects when providers are observed by enumerators (Leonard and Masatu, 2006), and how such effects dissipate over a short period of time. Our findings on suggestive evidence that providers modify behavior when they are aware of being observed by potential patients point to the need for further research on this explored aspect of factors that might influence quality of care.

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