Pre-analysis plan for "What drives poor quality of care for child diarrhea: A standardized patient experiment"

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Abstract

Diarrhea is the second leading cause of death for children around the world. This is true despite the fact that nearly all such deaths could be prevented with a simple and inexpensive solution: oral rehydration salts (ORS). Private health care providers, who treat the majority of childhood illness in low- and middle-income countries (LMICs), are particularly unlikely to dispense ORS to children with diarrhea. Instead, providers often dispense antibiotics inappropriately. However, there is no clear evidence on why ORS is under prescribed and antibiotics are over prescribed by private providers. In this study, we examine several leading explanations for poor quality of care for child diarrhea in the private sector. First, patient preferences for ORS alternatives (e.g., an antibiotic) could be driving under prescription of ORS. We identify the causal effect of patient preferences by having anonymous standardized patients (SPs) pose as caretakers of children with diarrhea and express different (randomly assigned) preferences for treatment (ask for ORS, ask for antibiotics, or let provider decide). Second, private providers could be responding to financial incentives to sell more profitable alternatives to ORS (e.g., an antibiotic). To estimate the causal effect of financial incentives, we randomly assign a subset of SPs to inform providers that they can get discounted treatments at a relative's drug shop rather than from the provider or local pharmacy. This eliminates the provider's financial incentive to recommend a given treatment and allows us to estimate the effect of such incentives on treatment. Finally, private providers might not directly distribute ORS or could have frequent stock-outs. To estimate the causal effect of stock-outs, we will randomly assign half of the providers to receive a three-month supply of ORS. This generates exogenous variation in stock outs and thus enables us to isolate the causal effect of stock outs on ORS and antibiotic prescribing.

[EXAMPLE TEXT OF HOW RESULTS WILL BE PRESENTED IN ABSTRACT OF PAPER]
When SPs let providers decide on treatment, xx% of SPs received ORS and yy% received antibiotics. Asking directly about ORS [increased/decreased] ORS dispensing by xx percentage points and [increased/decreased] antibiotics dispensing by yy percentage points. Asking about antibiotics [increased/decreased] ORS dispensing by xx percentage points and [increased/decreased] antibiotics dispensing by yy percentage points. This suggests that patient preferences [do/do not] play an important role in diarrhea care. SPs that informed the provider that they would purchase from a relative's drug shop were xx percentage points [less/more] likely to get ORS and yy percentage points [less/more] likely to get antibiotics, suggesting that providers [are/are not] responsive to financial incentives when treating child diarrhea. Combining causal estimates of the impact of each factor on prescribing, and population estimates of the prevalence of each factor, allows us to estimate the population level impact of implementing interventions that address each factor. We find that interventions targeting x, y and z will result in xx, yy zz more children getting ORS saving xxx, yyy, zzz young lives.

Introduction

Over 500,000 children die annually from diarrheal illness and over a quarter of these deaths occur in India.[1] Nearly all of these deaths are the result of dehydration, which is cheaply preventable and treatable with the use of oral rehydration salts (ORS).[2-6] Historically, ORS has been incredibly effective at reducing child mortality across the world and the World Health Organization and UNICEF now recommend ORS for all cases of child diarrhea regardless of illness severity.[7-9] Despite these facts, only about a third of child diarrhea cases are treated with ORS globally[10] and only half of cases in India received ORS[11].

Lack of access to health care certainly explains a portion of this underuse of ORS. However, most children visit a health provider for care, and even then, they often fail to be treated with ORS. A nationally representative survey from India shows that, in 2016, over 60 percent of children with diarrhea visited a health provider for treatment, while only 58 percent of these children in turn were treated with ORS.[11] This problem is more severe in the private sector where over 75% of treatment for child diarrhea occurs in India.

There is little evidence to date documenting why so many children fail to receive ORS when they visit a private health provider. Prior work documents that even when private providers know that ORS is the appropriate treatment for diarrhea, they still fail to prescribe it.[12] This implies that lack of knowledge is unlikely to be an important driver and educating providers is unlikely to increase ORS dispensing. For example, a recent study which surveyed providers in Gujarat, India reports that all providers visited for the study indicated ORS as part of their preferred diarrhea treatment regimen.[16] Moreover, ORS has been the gold standard treatment for child diarrhea for nearly 4 decades and successful social marketing campaigns have led to very high awareness.[13-15] In 2016, over 85% of women in India had heard of ORS.[11] Finally, several studies that focused on increasing provider knowledge as a means of improving ORS use have been ineffective.[17-19] If it is not the result of poor provider knowledge, then why do so many children that seek care in the private sector not receive ORS?

There are several remaining explanations. On the demand-side, caretakers could prefer antibiotics and other non-ORS treatments and providers could dispense such treatments even if they know it is inappropriate. We know from prior research that private providers are more concerned than public providers with patient satisfaction, possibly in an effort to retain market share.[20,21] Patients could prefer non-ORS treatments or dislike ORS for several reasons including poor taste (62% of caretakers in Uganda agreed with the statement "ORS tastes bad so your child won't take it")[22], little observable benefit to using ORS (ORS does not reduce the volume of diarrhea), and a perception that ORS is not a real medicine (its ingredients are predominantly water, sugar, and salts).

There are also two key supply-side mechanisms that could lead providers who know ORS is the correct treatment to prescribe something different. First, private providers could be responding to financial incentives to sell more expensive alternatives to ORS. There is a large body of literature documenting the responsiveness of health providers to financial incentives around the world.[23-25] ORS is relatively inexpensive and antibiotics or other treatments could generate more profit. There is evidence from China demonstrating that financial incentives faced by providers drive over-prescription of antibiotics for adults. Using a similar research design as our study, Currie et al. (2011 and 2014) used standardized patients in China to demonstrate that patient preferences had little effect on inappropriate antibiotic prescription and that the problem was mostly driven by the supply-side. Moreover, they find that overprescription only occurs when the provider has a financial incentive to do so.[26,27]

Second, private providers might not supply ORS on site or could have frequent stock-outs. As a result, providers might instead prescribe something they have available. Moreover, even if prescribed, the hassle of having to pick-up the ORS from a different location could dissuade retrieval. Wagner et al. (2014) documented that the public-private gap in ORS dispensing in India could be driven by the private sector's tendency to not have ORS available on site.[16]

In this study, we will use a randomized design to isolate the effect of patient preferences, financial incentives, and stock-outs on prescribing for child diarrhea in the private sector. To estimate the effect of patient demand on ORS and antibiotic prescribing and dispensing, we will have anonymous standardized patients (SPs) pose as a caretaker of a child with diarrhea. SPs will pose as three different types: *type-1* will request ORS to treat the diarrhea; *type-2* will be uncertain and follow provider recommendations; *type-3* will request an antibiotic. We will enroll 2,000 private providers across three states in India and randomly assign each to receive a visit from one of the three SP types. Comparison of these study arms will allow us to estimate the causal effect of patient preferences on ORS and antibiotic prescribing.

To identify the causal effect of financial incentives, we will add a fourth type of SP that will be identical to type-2 but will inform providers that they can get free treatments at a relative's drug shop. This eliminates the provider's financial incentive to recommend a given treatment and thus enables us to isolate the causal effect of financial incentives on ORS and antibiotic prescribing.

To estimate the causal effect of stock-outs, we will randomly assign half of the providers to receive a three-month supply of ORS. This generates exogenous variation in stock-outs and thus enables us to isolate the causal effect of stock-outs on ORS and antibiotic prescribing.

Combining causal estimates of the impact of mechanisms with the prevalence of each mechanism allows us to estimate the population level impact of implementing interventions that address each driver of poor quality of care for child diarrhea. For example, combining the causal effect of stock-outs on prescribing with data on the share of providers with stock-outs allows us to estimate the extent to which eliminating stock-outs will change ORS and antibiotic prescribing at the population level.

[INSERT SUMMARY OF FINDINGS]

Our study contributes to existing literature in several ways. First, we contribute to sparse evidence on what drives poor quality of care in LMICs. We know little about what drives quality of care in the private sector and why patients continue to seek care from health providers who provide poor quality care. Recent reports from the Lancet Global Health, the National Academies, and the World Health Organization highlight the urgent need for global quality improvements.[13-15] Das et al. show that quality is particularly poor in India and Mohanan et al. show that quality is poor even when knowledge is high. We show that [INSERT FINDINGS ON WHICH FACTORS ARE MOST IMPORTANT AND WHICH INTERVENTIONS ARE LIKELY TO BE MOST EFFECTIVE].

We also provide the most comprehensive evidence to date on why one of the most important health technologies in history is often not prescribed. There are several papers documenting the problem of suboptimal ORS prescribing but very little evidence documenting why this occurs. Our study suggests that the main drivers are [XX] and that interventions aimed at increasing ORS dispensing should focus on [XX]. If such interventions are targeted appropriately, millions of young lives could be saved.

We also contribute the literature on overuse of antibiotics. Antibiotic resistance is a global crisis and resistant infections claim hundreds of thousands lives each year worldwide. Currie et al. show that patient preferences and financial incentive both contribute to inappropriate antibiotic prescribing in China. We contribute to this work by focusing on child diarrhea in India, which accounts for large portion of global antibiotic prescribing. India had the fastest growth in antibiotic consumption from 2000 to 2010 and is now the biggest consumer of antibiotics in the world. Moreover, child diarrhea is one of the most common illnesses for which antibiotics are prescribed inappropriately and India accounts for the most cases of child diarrhea in the world. Thus, our study provides the most comprehensive evidence to date on why antibiotics are prescribed inappropriately in a setting that is the one of the largest contributors to antibiotic resistance.

Adoption of health technology has been studied in great detail in LMICs (e.g., bed nets, chlorine treatment, and immunizations). Dupas and Miguel (2017) provide summaries of this literature.[28,29] Our study will contribute in several ways. First, this literature predo+minantly focuses on adoption at the individual or household level (do individuals use a bed net or do households treat their drinking water). In contrast, our study will examine what influences take-up of ORS during a provider-patient interaction. Providers often act as gatekeepers to health technology. Thus, it is essential to understand what aspects of the provider-patient interaction lead to low take-up. Second, the few studies that examine provider-patient interactions focus predominantly on the supply-side, studying mechanisms such as provider knowledge[12,30-32] and misaligned financial incentives.[26,27,33] Only a small number of studies explore how demand-side factors impact health technology take-up during a provider-patient interaction and both do so in the context of technology that is *overused* (antibiotics and malaria treatment).[26,34] This study will be the first to examine if patient preferences lead to *underuse* of health technology. Finally, the evidence on the barriers to take-up of ORS, one of the most important medical advances in history,[35] is particularly limited.[14] Our study provides a new understanding of why adoption of ORS is so low even when children seek care from a provider.

This work also provides a novel and comprehensive approach for understand how specific mechanisms affect population health. By randomizing each mechanism and combining causal estimates with the prevalence of each mechanism we provide a more complete understanding of the extent to which each mechanism contributes to the problem.

RESEARCH DESIGN

Research Questions

We are primarily concerned with three broad research questions.

1. To what extent does patient demand drive inappropriate care for child diarrhea in the private sector?
2. To what extent do providers' financial incentives drive inappropriate care for child diarrhea in the private sector?
3. To what extent does lack of ORS supply in private clinics drive inappropriate care for child diarrhea?

Study Setting

This study will take place in two Indian States: Karnataka and Bihar. Bihar is one of the poorest states in India and is mostly rural. Karnataka has above average per capita income relative to other Indian states. In a 2016 nationally representative survey, 92% of child diarrhea cases in Bihar that sought treatment did so in the private sector, of which 51% were treated with ORS and 20% received antibiotics. In Karnataka, roughly half of cases sought care in the private sector, of which 67% received ORS and 13% received antibiotics. We chose states that are very different in SES and diarrhea care seeking to ensure our results are representative of a broad population. Assessing the barriers to ORS dispensing in these distinct settings will help with the generalizability of our results. While it is unclear if our results will generalize to other countries, India accounts for the most deaths from child diarrhea and the most antibiotic resistance.[41] This makes the Indian context important for global health even if results do not generalize to other countries.

Moreover, the private sector treats the majority of childhood illness and disproportionately fails to provide ORS in most developing countries.[42] Therefore, the context around diarrhea care-seeking and ORS dispensing in other developing countries is quite similar to the Indian context.

Table 2. SP Experimental Design

Type	Preferences	Financial Incentive?	Number of Visits*	
			Case 1	Case 2
Type-1	Ask for ORS	Yes	250	250
Type-2	Ask for Antibiotic	Yes	250	250
Type-3	Follow Provider's Advice	Yes	250	250
Type-4	Follow Provider's Advice	No	250	250

*Each of the 50 SPs will visit 40 providers creating 500 visits per Type (2,000 total visits). Cases 1 and 2 will vary on the severity of the diarrhea case. All cases will represent a case of rotavirus.

SP Experimental Design

We will enroll 2,000 private providers that care for children with diarrhea (sampling details below). Most providers will be single provider establishments, the most common type of facility from which Indian patients seek care for child health services.[11] Each provider will receive one visit from an enumerator posing as a caretaker for a child with a case of diarrhea (i.e., standardized patients or SP). We will randomly assign providers to receive a visit from one of four different SP-types. The types are designed to estimate the effect of patient preferences on prescribing. **Type-1** SPs will request ORS to treat the child's diarrhea and will purchase ORS if available (unless the provider recommends against ORS) plus whatever else the provider recommends. **Type-2** SPs will request antibiotics, and purchase antibiotics if available (unless the provider recommends against it) plus whatever else the provider recommends. **Type-3 and Type-4** SPs will both have no treatment preferences and will rely only on the provider's recommendation. Type-3 will purchase whatever treatments the provider recommends. However, Type-4 will inform the provider that they only want a treatment recommendation (i.e., they will not purchase any treatment) because *their child is in a different town and their spouse needs to know what to purchase from the pharmacy*. They will claim the doctors in their town are not very knowledgeable about treatment and they want a recommendation from a professional. This design attempts to eliminate any influence of financial incentives in the provider's recommendation for Type-4 SPs. All SPs (including Type-4) will pay any fees required to see the doctor. We will also vary the severity of the case of diarrhea presented by the SPs. This serves two purposes: 1) it limits the possibility that providers catch on to the experiment and 2) it gives our results more external validity, because our estimates will apply to a variety of cases instead of one specific case.

Comparing ORS and antibiotic dispensing/prescription across the different types addresses several research questions.

<u>ORS dispensing/prescribing as outcome:</u>

1. Type-1 vs. Type-3: *To what extent is ORS dispensing/prescribing sensitive to* ***patient demand****?*
2. Type-2 vs. Type-3: *To what extent does patient demand for inappropriate antibiotics* ***crowd out*** *ORS dispensing/prescribing?*
3. Type-3 vs. Type-4: *To what extent is ORS dispensing/prescribing sensitive to* ***financial incentives****?*

<u>Antibiotic dispensing/prescription as outcome:</u>

4. Type-1 vs. Type-3: *To what extent does patient demand for ORS* ***crowd out*** *inappropriate antibiotic dispensing/prescribing?*
5. Type-2 vs. Type-3: *To what extent is inappropriate antibiotic dispensing/prescribing sensitive to* ***patient demand****?*
6. Type-3 vs. Type-4: *To what extent is inappropriate antibiotic dispensing/prescribing sensitive to* ***financial incentives****?*

If there is no difference in ORS or antibiotic dispensing between Types 1, 2, and 3, this suggests that under-dispensing of ORS and over-dispensing of antibiotics is not driven by patient preferences and is likely driven by supply-side factors.

Fifty enumerators will carry out these SP visits. We will extensively train each enumerator to play all 4 of the roles outlined in Table 2. If enumerators only played one role, then it is possible differences in enumerator traits confound our estimates of the effect of patient's requesting different medicines. Actors will carry out 10 visits of each type. This will allow us to include SP fixed-effects in our regression models, which will account for fixed differences between SPs. We will also have two different cases that will reflect different levels of diarrhea severity. Scripts will be identical across the different SP-types and cases aside from the elements we want to vary (treatment request and severity of symptoms). We will stratify random assignment of SP-types by case-types to ensure cases are equally paired with the different SP preferences (see Table 2). This ensures that differences in case types do not confound our estimates of the impact of patient preferences. All cases will be for a child aged 2 years old; old enough to express symptoms verbally but young enough to be at high risk of mortality from diarrhea. As in previous studies, we will design both cases to reflect the symptoms of rotavirus infection for which treatment guidelines consist of ORS to prevent dehydration and zinc to reduce illness severity.[43] Antibiotics are ineffective for a case of rotavirus.

SPs will visit providers *without* a child. This pattern of health care, in which a family member seeks care on behalf of the sick patient, is common in India and enables use of SP methods without putting a child at risk. Some providers will likely ask that the SP return with the child (about 10% of providers did so in previous work).[36] This situation will not affect measurement or analysis of ORS dispensing because the provider should still dispense ORS to the SP in this situation. This complicates analysis of antibiotics because providers might prefer to examine the child before dispensing antibiotics. Thus, we will conduct robustness checks where we restrict to providers that did not ask the SP to return with the child when analyzing antibiotics as an outcome. It also is possible the provider providers a different recommendation for treatment when the child is present. We will assess the extent to which not having the child present could bias our results in several ways.

1. We will document the frequency that real caretakers seek care without a child from private providers in a household survey
2. We will ask providers about the frequency of care seeking without a child and whether this changes the way they recommend treatment.
3. Will use data from our household survey to identify providers who recently received a visit from a caretaker with a child. We will make sure to have an SP go to this same provider and compare data between the household and SP. We will do this for as many SPs as we can and compare treatment outcomes between real caretaker with the child and the SP
4. We will use provider survey vignette to compare stated treatment actions for patients with and without a child (half of vignette profiles have a child present and half do not).
5. We will compare the effects of SP preferences on prescribing to the effect of different patient preferences presented to the provider in vignettes (vignettes will vary whether the hypothetical patient requests ORS, requests antibiotics, or lets the provider decide).

Validity of SP Method

The SP method is an established and valid method for practitioner performance measurement because it presents a well-defined incognito case in a clinically accurate and consistent manner to all practitioners.[44-47]. This method has several benefits. First, it ensures illness and patient characteristics are identical across providers, which limits concerns about differential patient sorting across clinics, as might be the case when observing real patient-provider interactions. Second, because we know the actual illness being presented and the optimal care associated with the case, we can objectively score the quality of care provided. Finally, there are no concerns about Hawthorne effects because providers are unaware that the visit is being studied. This is particularly important because providers often behave differently in practice than they report in a vignette.[19,49] One common concern about the SP method is that providers will "catch on" and provide different care to our SPs than they would real patients. In practice it is rare that SPs are discovered. We will assess the extent to which they were discovered by 1) asking SPs whether they thought the provider knew they were not a real patient, and 2) asking the provider after the SP visit whether they thought any of their recent patients were fake patients and to describe what the fake patient will look like. If they describe a patient that fits our SP role, we will record this visit as having been found out. In a robustness check, we will exclude all such cases that we code as being found out.

ORS Supply Experimental Design

In addition to the SP experiment, we will layer on an experiment where we randomly assign free supply of ORS to half of the enrolled providers (Table 3). Assignment of ORS supply will be orthogonal to SP-type assignment (i.e. half of the visits in each cell in Table 2 will be with a provider assigned to increased supply). ORS supply assignment will be clustered at the town level. Towns generally include businesses and commerce that serve a collection of villages. Each town can be considered a separate health care market and assigning supply at the town level will mitigate spillover of free ORS supply to control providers. This experiment builds on our previous work which highlighted lack of ORS availability in the private sector as a potential barrier to use.[16] This work documented that only 35% of providers visited in Gujarat had ORS available on site. Moreover, according to a 2012 market analysis, 50% of 300 private providers surveyed in Uttar Pradesh had ORS stocked, 12% were out of stock, and 38% never had ORS stocked. Common reasons for not stocking ORS were low patient demand (35%) and low profit margin (15%).[50] Our intervention is expected to create an exogenous increase in the share of providers that have ORS stocked. Comparison of the providers that received increase supply relative to the provider that did not will identify the intention-treat-effect of increased supply. We will use an instrumental variables approach to estimate the impact of actually having ORS supply vs. not having supply (see below).

Table 3. ORS Supply Experimental Design

Increased Supply?	Number of Providers	Number of Visits
Yes	1,000	1,000
No	1,000	1,000

We will distribute roughly one month's supply of ORS to providers assigned to received increased supply and we will ensure that all SP visits are conducted before this supply is expected to run out. Supply will be distributed free of charge and providers will be asked to dispense to their patients as they see fit, but not to give it away to other providers. We will dispense 80 sachets of ORS to each provider, which is enough for them to treat more than one diarrhea case per day prior to our SP visit. All standardized patient visits will be conducted within three weeks of the roll-out of the supply intervention to ensure that facilities assigned to receive free ORS still have it in stock.

It is possible that providing free ORS supply to providers will incentivize ORS dispensing beyond the effect of having ORS available. For example, a provider that already had ORS stocked might be more likely to dispense ORS after receiving free increased supply. Thus, this would not capture the stock-out effect, but some other supply effect. However, this goes against neoclassical economic theory, which predicts that providers will sell the product that maximizes profits. If the profits from ORS are lower than the profits from other treatments, providers would still have a financial incentive to sell these other treatments (we will ensure that providers understand that the free ORS distribution only happens once). In practice, people do not always adhere to the neoclassical model. We will test for this by creating three subgroups of providers: 1) providers that never dispense ORS directly to patients, 2) providers that sometimes dispense ORS but were out of stock at baseline, and 3) providers that had ORS in stock at baseline. We will assess how ORS supply impacts ORS dispensing separate for each of these three types of providers.

SAMPLING AND DATA COLLECTION

Sampling

We will first select districts prioritizing those with high diarrhea prevalence in the most recent Demographic and Health Survey. We will start with the district with the highest diarrhea prevalence and sample all towns in that a district. Sampling of towns will be based on a local directly of towns. We will continue this process until we enroll 2000 providers. We will then sample all private providers who report treating cases of diarrhea in each town we visit. We will exclude very large towns (more than 100,000 people) because surveying all providers is infeasible. We will also exclude very small towns (less than 5,000 people) because they are likely to have too few providers. Most private providers in India run their own single-provider clinics. For clinics with multiple providers, we will only select one of the providers to survey. During recruitment, we will acquire informed consent from the provider to participate in the study. Informed consent will make providers aware that someone from the study team will visit them in the future to collect data on dispensing habits, but we will not disclose that this person will be an anonymous SP.

Household surveys

The team will conduct a household survey with 3-5 households per town with a child under-5 who had a case of diarrhea within the last 4 weeks (roughly 1,500 total). Households without a recent child diarrhea episode that sought care from a provider will not be surveyed. The interviewer will survey the primary caretaker of child/children under-5 in the household. The interviews will last 45 to 60 minutes and will ask about recent visits to health clinics for diarrhea as well as other things. During the interviews, the team will record the providers from which the caretaker sought treatment, which will help identify private providers for study enrollment. Key variables that will be measured in the household survey include:

1. If the caretaker requested any specific treatment, and if so which one(s)

    a. This will be used to bin caretaker into the different types of patients we are examining with the SP experiment
2. Assessment of the quality of care and customer satisfaction of their most recent visit
    a. This will be used in an analysis of how the market rewards quality of care. This will help us understand if misaligned market incentives (e.g. if the market does not reward quality) could partially explain persistent poor quality of care.
3. Discrete choice experiment about caretaker preferences for providers
    a. This will be used to assess which provider characteristics patients value the most (technical quality, interpersonal quality, price, medicines prescribed, caste/religion, and convenience).

A key objective of the household survey is to bin caretaker into the different types of patients we are examining with the SP experiment (item 1 above). To estimate the contribution of preferences on inappropriate prescribing, it is essential to measure the real distribution of patient types. For example, if a large share of patients requests antibiotics (type-2), and requesting antibiotics substantially reduces ORS dispensing (type-2 compared to type-3), then this suggests that patients requesting antibiotics explains a large portion of inappropriate antibiotic prescriptions. Conversely, if only a small share of patients requests antibiotics, then patient demand for antibiotics can only explain a small portion of inappropriate treatment even if the effect of requesting antibiotics is large.

Provider survey

During provider recruitment we will conduct a survey of each provider, which will collect information on provider characteristics (e.g., age, degree), case-load, drug inventory and prices, and provider beliefs about diarrhea treatment. The survey will also include a vignette to test providers' knowledge about proper diarrhea treatment guidelines. Data collected in the provider survey will be used to measure how frequently providers do not have ORS available on site. ORS supply will be dispensed to a random subset or providers directly after the provider survey. During the provider survey we will also conduct a discrete choice experiment where the provider is given hypothetical patient profiles that matches our SP profiles. Providers will then be asked to choose which treatment to provide each profile. This provider DCE will be used to compare how providers say they will respond to patient preferences to hypothetical patients with how they actually respond to SP preferences.

Standardized patients

SP visits will take place during the three months following the provider survey. Seventy enumerators evenly distributed across the three states will undergo two weeks of intensive training on the different roles. At the end of the training, we will select the top 50 enumerators to serve as SPs and the remaining 20 will be serve as substitutes if any of the top 50 drop out. The study team will train enumerators extensively during these two weeks so that each role is portrayed consistently across enumerators. This will include memorizing answers to common questions (e.g., “when was the last time the child had diarrhea?”, has the child been exposed to mosquitos recently?”, or “are any of the other children in the house sick?”) so that each enumerator responds similarly for the respective role. In addition, enumerators will be trained on what to look for during each visit and how to record data about the visit on tablet devices using SurveyCTO software.

Once SPs are comfortable with their roles, they will each conduct practice visits with 5 providers that are not enrolled in the study. This will help identify questions that were not prepared for during training and give the enumerators a chance to play their role in a real-life setting. We will have a debriefing after the practice visits to fine tune all of the roles.

When roles are finalized, SPs will begin making the visits to the enrolled providers. Before the SP visits begin, we will create a schedule for each enumerator that includes 1) the providers to visit on each day and 2) the role to play (type-case combination from Table 2). The schedule will be based on each provider’s random assignment.

SPs will use a mobile device to fill out a detailed form after each provider visit that will document several aspects of their interaction with the provider. This will include the treatment(s) the provider recommended, the treatment(s) the SP acquired, whether the treatment requested was out of stock, and the price of any products purchased. In addition, we will record whether or not the provider recommends the caretaker uses ORS and/or antibiotics (even if they don’t have it in stock).

Summary of Data Sources	
Data Source	**Key Outcome**
Household Surveys	Distribution of patient types 1, 2, and 3 (from Table 2) in real population
Provider Survey	Prevalence of stockouts at baseline, provider knowledge
SP Visits	Dispensing of ORS and Antibiotics
Provider follow-up	Prevalence of stockouts at time of SP visit

Follow-up survey with provider

After the SP visit (same day or day after), our study team will follow up with the provider to assess 1) whether the provider has ORS in stock and 2) whether the provider expected that they received a visit from a fake patient recently. Measuring ORS supply with this follow-up visit will be important for assessment of the stock out effect because the SPs themselves will not be able to measure inventory of treatments when they come to the clinic. This will allow us to assess whether the provider had ORS in stock at the time of our SP visit and to assess the extent to which our ORS supply intervention affected the prevalence of stock-outs.

Primary Outcomes

The two primary outcomes will be whether the SP received ORS and whether the SP received an antibiotic. For our primary analyses we will classify a treatment as being received if the provider *dispensed*, *prescribed, or recommended* the treatment to the SP. This measures a provider's behavior which the margin on which we are intervening. In a secondary analyses, we will code a treatment as received in two different ways. First, we will set the outcome to 1 if a provider either *dispensed the treatment* OR *prescribed the treatment AND the SP was able to retrieve the treatment from the pharmacy recommended by the provider*. This coding has more public health relevance because it more accurately measures whether the patient could acquired the treatment. Second, we will code the outcome as 1 only if the provider directly dispense the treatment to the SP. This is important because qualitative evidence suggests that patients sometimes do not take the extra step to retrieve ORS from pharmacies when prescribed.

Secondary Outcomes

In addition, we will assess whether the provider dispensed/recommended the following treatments: 1) any zinc, 2) zinc in combination with ORS (the WHO recommended treatment), 3) ORS and no antibiotics, and 4) ORS + zinc and no antibiotics (the gold standard). We will also assess the total number of prescriptions.

While the goal in the global health community is to promote use of both ORS and zinc, we chose to focus our SP experiment on ORS use with or without zinc for several reasons. First, although zinc compliments ORS with additional health benefits, zinc alone is far less effective than zinc in combination with ORS. ORS, however, is incredibly effective even without zinc.[6] Second, ORS has been around for several decades and global use has been stagnant since 2005.[10] However, zinc is relatively new and worldwide use has been growing as awareness spreads. This suggest that simply expanding awareness could improve zinc dispensing whereas increasing ORS dispensing requires novel and targeted interventions. Third, we found through prior studies that zinc use is very low in our study setting. In one study, we found that 0 of 178 providers dispensed zinc to an SP.[12] It is necessary that we have sufficient variation in our outcomes in order to detect differences across SP types, which has not been present for zinc in our other studies. Finally, additional SP arms that focus on zinc preferences would require an expanded sample size and increase the overall cost and complexity of the design.

Measuring Stockouts

One goal of the ORS supply intervention is to eliminate ORS stockouts and increase the likelihood that clinics/pharmacies have ORS available to dispense on site. The primary way we will measure whether ORS is in stock will be to ask providers whether they have ORS available on site to dispense to patients. Some providers will have an attached pharmacy and thus might not have ORS available themselves but instead have it available in the attached pharmacy. In secondary analyses, we will code a provider as having ORS in stock if 1) the provider has ORS available to dispense directly or 2) the attached pharmacy has ORS available to dispense. We will measure stockouts at baseline (prior to the ORS supply intervention and the SP visits) and immediately after the SP visit.

EMPIRICAL STRATEGY

Estimating the causal effect of patient demand on ORS and antibiotic prescribing and dispensing

To examine the impact of patient demand on a providers' decision to dispense treatment, we will compare treatment outcomes for Type-1 (ask for ORS), Type-2 (ask for antibiotic), and Type-3 (let provider decide) SPs. We will pool both case severity types (Table 2). We will estimate the following equation.

(1) $$y_{isr} = \beta_0 + \beta_1 AskORS_{isr} + \beta_2 AskAnti_{isr} + \beta_3 Supply_{is} + \beta_4 Severe_{isr} + \theta_s + \epsilon_{isr}$$

The unit of observation in this equation is a provider-SP visit, and y_{isc} represents whether a respective treatment was prescribed (ORS or antibiotics) by provider i to SP s of role r. $AskORS$ is an indicator for whether the observation is from a Type-1 SP and $AskAnti$ is an indicator for whether the observation is for a Type-2 SP. The $Severe$ term is an indicator for whether the observation is from an SP presenting case 2 (more sever) rather than case 1 (less sever). The $Supply$ term is indicator for whether the provider was assigned to the free ORS supply arm. SP type assignment will be stratified by case severity and ORS supply, so these terms serve to improve precision but should not affect our other estimates. The terms β_1 and β_2 represent the impact of a patient requesting ORS or requesting antibiotics relative to a patient not requesting anything and following the provider's advice. Type-4 SPs visits will be excluded from this analysis. We will conduct secondary analyses where we pool Type-3 and Type-4 SPs (to improve statistical power), in which case the provider's recommendation will be the outcome (no purchases will be made by Type-4 SPs). We will estimate Huber-White robust standard errors. We will not cluster standard errors because our treatment assignment (visits from different types of SPs) is not clustered.[50]

We will also explore the interaction of both case severity and ORS supply with patient preferences in separate models.

(2) $$y_{isr} = \beta_0 + \beta_1 AskORS_{isr} + \beta_2 AskAnti_{isr} + \beta_3 Severe_{isr} + \beta_4 Supply_{is} + \beta_5 AskORS\ X\ Supply_{isr} + \beta_6 AskAnti\ X\ Supply_{isr} + \theta_s + \epsilon_{isr}$$

(3) $$y_{isr} = \beta_0 + \beta_1 AskORS_{isr} + \beta_2 AskAnti_{isr} + \beta_3 Severe_{isr} + \beta_4 Supply_{is} + \beta_5 AskORS\ X\ Severe_{isr} + \beta_6 AskAnti\ X\ Severe_{isr} + \theta_s + \epsilon_{isr}$$

Where β_5 and β_6 represent the different effect of asking for ORS and asking for antibiotics based on whether the provider was part of the ORS supply intervention (equation 2) and whether the SP's case presented was more severe (equation 3). We expect that asking for ORS will be more effective when the provider received free ORS supply (i.e. β_5 will be positive in equation 2) and providers will be less sensitive to patient preferences when the case more severe (i.e. $\beta_5$and β_5 will be negative in equation 3).

Recent research highlights that fully interacted models are yield more appropriate inference in cross-cuting RCT designs when there are interactions between intervention arms. In our case, we are crossing the preference treatments, the severity treatment, and ORS supply treatment. We chose to not use the less precise fully interacted models as our primary analysis because in our case the effect size of patient preferences when averaged across ORS supply arms is still a relevant scenario. This would be the effect when ORS supply is somewhere in between baseline levels and when ORS is dispensed for free. Similarly, the effect size of patient preferences when averaged across severity arms is also relevant (i.e., the effect size when severity is somewhere in between our severe and not severe case).

Commented [ZW1]: Cite Karthik paper

Estimating the causal effect of financial incentives on ORS and antibiotic prescribing and dispensing

To examine the role of financial incentives on ORS and antibiotic prescription, we will compare treatment recommendations between Type-3 and Type-4 SPs. The only difference between these two types is that Type-4 informs providers that they will not purchase the recommended treatment(s) from the provider. Thus, the difference between these two groups isolates the effect of financial incentives on provider recommendations. We will estimate the following equation using only Type-3 and Type-4 SP visits:

(4) $$y_{isr} = \beta_0 + \beta_1 NoFinInc_{isr} + \beta_2 Severe_{isr} + \beta_3 Supply_{is} + \theta_s + \epsilon_{isr}$$

The outcome in this case, y_{isr}, represents whether a treatment was dispensed OR recommended by provider i to SP of type r. $NoFinInc$ is an indicator for whether the provider had a financial incentive with this SP (i.e. they were a type-4 SP rather than a type-3 SP). The coefficient of interest, β_1, represents the impact of removing financial incentives on treatment recommendations across all providers. We will also run an additional specification where we interact $Supply$ with $NoFinInc$ to test whether financial incentives have a different effect when providers were given free ORS supply.

Some providers might not dispense medication or might not have higher profit margin for antibiotics compared to ORS, thus our average treatment effect will be a lower bound of how financial incentives impact ORS dispensing for a provider who has financial incentive to dispense one treatment over another. To better understand this, we will also look at heterogeneity based on the following domains:

1. Did the provider dispense medication directly to patients (or do they have an attached pharmacy that is part of their business)?
2. Was the profit margin for antibiotics larger than ORS?

We expect that the effect of removing financial incentives will be larger for providers that dispense their own medication and that have a higher profit margin for antibiotics than for ORS.

Estimating the causal effect of stock-outs on ORS and antibiotic prescribing and dispensing

To examine the intention-to-treat (ITT) effect of receiving free ORS supply on treatment dispensing, we will compare the 1,000 providers who were assigned to received increased ORS supply to the 1,000 who were not. This is estimated with β_4 from equation 1, but with standard errors clustered at the town level. While the ITT effect is important for understanding the impact of an intervention that provides free ORS to private providers, we are also interested in the effect of having ORS stocked on ORS prescribing (e.g., are providers less likely to prescribe ORS if they do not have it available on site?). The ITT effect will underestimate the average treatment effect if many providers would have ORS in stock in absence of the intervention. To estimate the local average treatment effect of having ORS in stock, we will use a two-stage least squares (2SLS) approach, using random assignment as an instrument. We will estimate the following two stages:

(5) $$Stock_{isr} = \lambda_0 + \lambda_1 AskORS_{isr} + \lambda_2 AskAnti_{isr} + \lambda_3 Severe_{isr} + \lambda_4 Supply_{is} + \theta_s + \epsilon_{isr}$$

(6) $$y_{isr} = \beta_0 + \beta_1 AskORS_{isr} + \beta_2 AskAnti_{isr} + \beta_3 Severe_{isr} + \beta_4 \widehat{Stock} + \theta_s + \epsilon_{isr}$$

In equation 5, $Stock_i$ indicates whether provider i had ORS in stock during the visit from the SP (or if it was available in the attached pharmacy). ORS stock will be recorded after the SP visit during the provider follow-up survey. The term $Supply$ indicates whether the provider was randomly assigned to receive increased ORS supply. We expect that λ_1 will be positive because the intervention will increase the probability that a provider has ORS in stock.

In equation 6, y_{isr} is the same as equation 1. $\widehat{Stock}$ in this equation represents the predicted probability of stock-outs from equation 5. Therefore β_4 in equation 6 represents the local average treatment effect (LATE) of having ORS stocked on treatment outcomes. This analysis assumes that 1) assignment to receive ORS supply does not directly affect treatment outcomes (aside from through having ORS in stock) and 2) assignment to receive ORS supply is not correlated with the error term in equation 4. Because assignment is random, these exclusion restrictions will be satisfied in expectation. We will cluster standard errors by town in this analysis because ORS supply is assigned at the town level.

One potential violation of the exclusion restriction is that assignment to the ORS supply arm could affect ORS dispensing through other mechanisms aside from stock outs. First, providers who do not dispense ORS at baseline could increase ORS prescribing because they can now sell it directly to the patient and make a profit. Second, having ORS available could increase the salience of ORS, particularly in clinics where ORS is not usually available. To address these potential concerns, we will also conduct our 2SLS model restricting only to providers who reported dispensing ORS at baseline.

We will also interact SP type assignment with $Supply$ in equation 5 and $\widehat{Stock}$ in equation 6 to estimate heterogeneity in the LATE for each SP type.

Heterogeneity

We will look at heterogeneity by several domains to help understand the mechanisms that are driving our main effects:

1. *Urban/rural*: We expect that providers are more responsive to patient demand in urban areas because there is more competition and thus more incentive to appease patients to ensure they return. We expect that ORS supply will have a larger effect in rural areas where access to supply chains is more limited.
2. *Market competition*: We expect that provider are more responsive to patient demand in areas where the market is more competitive (i.e., more alternatives to choose from). We will define market competition as the number of private providers per in a town. We will record the number of private providers in each town we sample.
3. *Whether provider dispenses medication*: Providers who dispense medication are likely to response differently to our interventions. Prescribing behavior of providers who do not dispense medication will be less responsive to financial incentives and might be more responsive to receiving ORS supply.
4. *Whether provider has ORS available to dispense at baseline*: We expect the ORS supply intervention to have a particularly large effect when the provider does not have ORS available to dispense at baseline.
5. *Facility type*: We will categorize facilities that are private doctors' offices without an accompanying pharmacy, facilities where doctors' offices are attached to a pharmacy in the same

building, and facilities that are only pharmacies. These different facility types might respond to financial incentives, patient preferences, and ORS supply differently.

6. *Knowledge of ORS at baseline*: We expect that providers who report correct treatment in the provider survey vignettes will be more responsive when patient ask for ORS.
7. *Qualifications of the provider*: We expect that providers with higher qualifications will be less responsive to patient preferences.
8. *State*: We will compare results in Bihar to results in Karnataka. We expect the results in Bihar to be more pronounces because this state is more poor and rural and providers generally have less training.

Selecting Covariates for Adjusted Models

In addition to the unadjusted models described in equations 1-6, we will also present all regression models including a set of covariates to improve precision of our estimates and to adjust for any chance confounding. We will start with a broad set of geographic and provider level covariates that we expect to be predictive of prescribing behavior. We will then use a (yet to be determined) machine learning technique to identify the set of covariates that are most predictive of the outcome. This will either be double LASSO or a k-fold cross-validation technique.

Estimate how interventions aimed at eliminating different barriers contribute to changes in ORS and antibiotic prescribing at the population level

Once we identify the effect of each mechanism on diarrhea treatment dispensing (using the experiments) and the prevalence of stockouts and patient preferences (using the household and provider surveys), we can use this information to simulate the effect of eliminating or reducing different barriers to appropriate care. Moreover, we can estimate how each mechanism contributes to population level under-dispensing of ORS and over-dispensing of antibiotics.

Interventions that target demand generation: Equation 1 will provide the probability of ORS and antibiotic dispensing and prescribing for patients with different preferences. The household survey will provide the share of patients that can be categorized as each preference type. This will allow us to fill in the parameters listed in table 4. The term β_0 represents the probability of ORS dispensing/prescribing for patients that do not request any specific treatment (the constant from equation 1 with $Case2$ and $Supply$ terms omitted). The β_1 and β_2 terms represent the change in probability of prescribing if patients instead request ORS or antibiotics in equation 1. The sT terms represent the share of patients that are of each type estimated using the household survey. We can use this information to simulate the population level effect of an intervention that shifts people from requesting antibiotics to requesting ORS:

Status quo ORS dispensing/prescribing at the population level:

(8) $(\beta_0 + \beta_1) * sT1 + (\beta_0 + \beta_2) * sT2 + \beta_0 * sT3 = P$

Population level ORS dispensing/prescribing if λ caretakers switch to requesting ORS instead of requesting antibiotics:

(9) $(\beta_0 + \beta_1) * (sT1 + \lambda) + (\beta_0 + \beta_2) * (sT2 - \lambda) + \beta_0 * (sT3) = P^*$

In equation (6), P is the fraction of all patients that are dispensed/prescribed ORS under the status quo. In equation (7) we introduce the term λ, which represents the quantity of patients that were shifted from requesting antibiotics to requesting ORS. Therefore, P^* is the fraction of patients that would receive ORS if the share of patients that are type-1 increased by λ and the share of patients that are type-2 decreased by λ. The difference between P^* and P is the population level increase in ORS dispensing by such a shift. We will estimate P^* under a range of λ values and compare to effect sizes of studies that evaluate interventions aimed at increasing ORS use.[14]

Table 4. Parameters used to simulate overcoming patient demand barriers to ORS dispensing

	Patient Type		
	Type-1	Type-2	Type-3
Pr(ORS)	β_0+β_1	β_0+β_2	β_0
Share of Population	sT1	sT2	sT3

β parameters estimated from equations 1 (with Case2 and Supply terms omitted)

Share parameters estimated through client exit interviews

T = Type; s = share

To estimate the total contribution of patients requesting antibiotics on underprescribing of ORS and overprescribing of antibiotics at the population level, we will set λ equal to sT2. This will simulate ORS and antibiotic prescribing if all patients that currently request ORS instead request antibiotics. Similarly, to quantify the population level contribution of patient preferences, we will assume that sT1 and sT2 are both zero and that sT3 is 100%. This will simulate ORS and antibiotic prescribing if patients always relied on provider recommendations. Comparison with the status quo estimates the contribution of patient preferences on population level ORS dispensing/prescribing.

This is a simplified example and it is possible that patients are both type-1 and type-2 and thus sT1 + sT2 + sT3 could add up to more than 100%. To address this, when analyzing ORS as an outcome we will categorize patients that ask for ORS and antibiotics as type-1 (asking for ORS) and when antibiotics as an outcome we will categorize such patients as type-2 (asking for antibiotics). This assumes that asking for ORS and asking for both ORS and antibiotics have the same effect on ORS. To test the robustness of this assumption, we will conduct sensitivity analysis where we will vary the potential effect of asking for both treatments on ORS and antibiotics dispensing.

Interventions to decrease the financial incentive of providing ORS alternatives: β_1 from equation 2 represent the intention to treat effect of removing financial incentives from a provider's decision to dispense ORS (among providers with and without a financial incentive). Thus, this estimate represents the contribution of financial incentives to under-dispensing of ORS and over-dispensing of antibiotics and mimics the effect of an intervention that eliminates financial incentives.

Interventions that increase supply of ORS: We will use the 2SLS estimates from equation 4 to simulate the effect of interventions that increase the share of providers with ORS available on-site (table 6). We will estimate the following.

Status quo ORS dispensing/prescribing:

(10) $(\beta_0 + \beta_1) * sS + \beta_0 * sNS = P$

ORS dispensing/prescribing if quantity of providers with ORS in stock increased by λ:

(11) $(\beta_0 + \beta_1) * (sS + \lambda) + \beta_0 * (sNS - \lambda) = P^*$

The difference between P and P^* represents the increase in population level ORS prescribing if an intervention increased the fraction of private providers with ORS available on site by λ. If we set λ equal to the share of providers without ORS available on-site (sNS), this simulates ORS dispensing/prescribing if all providers has ORS in stock. Comparison of this estimate with the status quo estimates the contribution of ORS stock-outs on population level ORS dispensing/prescribing.

Table 6. Parameters used to simulate overcoming stock-out barriers to appropriate care for child diarrhea

	Provider Type	
	ORS in Stock	ORS Out of Stock
Pr(ORS)	β_0+β_1	β_0
Share of Population	sS	sNS

Beta parameters estimated from 2SLS in equation 4
Share parameters estimated through provider survey
S = ORS in Stock; NS = ORS out of stock; s = share; p = probability of ORS dispensing/prescribing

Power Calculations

For our power calculations, we focused on detecting differences in ORS dispensing between the four SP-types. We will have 500 SP visits per SP-type. This allows us to detect a difference of 8.8 percentage points off of a base of 50% (power of 0.8). In other words, our sample size will allow us to detect effect sizes that are plausible and to rule out large effects if our results are not significant. We will have more power for our analysis of the impact of increasing ORS supply because there are only two arms instead of four. For this analysis, we will be able to detect a difference in ORS dispensing of 6.2 percentage points.

Results

Summary statistics and balance

We will start by presenting a balance table to assess whether there are any important differences between providers assigned to the different arms. We will include characteristics measured from the provider survey. We will present means in table 1 and also use equation 1 to regress each characteristic on treatment assignment (mimicking how we will assess our primary outcomes).

Table 1. Provider characteristics (balance between study arms)

	Patient Preferences				
	(1)	(2)	(3)	(4)	(5)
	No preference	Asked for ORS	Ask for antibiotics	No preference and purchase elsewhere	P-value of joint test for orthogonality
Age					
Male					
Qualifications					
Number of patients per day					
Number of diarrhea case per month					
Yeas of experience					
Works at other facility					
Number of beds					
Dispenses medications					
ORS available at baseline					
Knew ORS was correct treatment					
Has electricity					
Consultation Fee					
Fee for ORS (if available)					
Fee for antibiotics (if available)					

Notes: This table will present the means from the provider survey for each of the outcomes listed in the far-left column. We will conduct t-tests to assess statistical differences between columns 2, 3, and 4 relative to column 1 and column 6 relative to column 5. We will also regression each outcome using equation 1.

Table 2. Provider characteristics (balance between study arms)			
	(1)	(2)	(5)
	Status Quo ORS Supply	Free ORS Supply	P-value of joint test for orthogonality
Age			
Male			
Qualifications			
Number of patients per day			
Number of diarrhea case per month			
Yeas of experience			
Works at other facility			
Number of beds			
Dispenses medications			
ORS available at baseline			
Knew ORS was correct treatment			
Has electricity			
Consultation Fee			
Fee for ORS (if available)			
Fee for antibiotics (if available)			
Notes: This table will present the means from the provider survey for each of the outcomes listed in the far-left column. We will conduct t-tests to assess statistical differences between columns 2, 3, and 4 relative to column 1 and column 6 relative to column 5. We will also regression each outcome using equation 1.			

Outcomes by study arm

We will present the mean for each of our outcomes for each study arm in tables 3 and 4. We will assess statistical significance using t-tests relative to no preference in table 3 and relative to no free supply in table 4. When assessing the impact of the ORS supply intervention in table 4, we will cluster standard errors by town.

Table 3. Share of visits with different treatment outcomes by study arm				
	Patient Preferences			
	(1)	(2)	(3)	(4)
	No preference	Asked for ORS	Ask for antibiotics	No preference and purchase elsewhere
Treatments dispensed or prescribed				
ORS				
Antibiotics				
Zinc				
ORS + Zinc				
ORS and no antibiotics				
ORS+zinc and no antibiotics				
Total number of treatments				
Notes: This table will present the means from the SP visits for each of the outcomes listed in the far-left column. We will conduct t-tests to assess statistical differences between columns 2, 3, and 4 relative to column 1 and column 6 relative to column 5.				

Table 5. Share of visits with different treatment outcomes by study arm		
	Provider Assigned Free Supply?	
	(1)	(2)
	No	Yes
Treatments dispensed or prescribed		
ORS		
Antibiotics		
Zinc		
ORS + Zinc		
ORS and no antibiotics		
ORS+zinc and no antibiotics		
Total number of treatments		
Notes: This table will present the means from the SP visits for each of the outcomes listed in the far-left column. We will conduct t-tests to assess statistical differences between columns 2, 3, and 4 relative to column 1 and column 6 relative to column 5.		

Regression results for equation 1 (patient preferences and ORS supply)

We will present regression results for equation 1 in Table 6. When assessing ORS dispensing/prescribing, we expect to find a positive and significant coefficient on "ask for ORS" and a negative and significant coefficient on "ask for antibiotics". This will imply that provider dispensing of ORS is sensitive to patient preferences. When assessing antibiotics dispensing/prescribing, we expect to find a negative and significant coefficient on "ask for ORS" and a positive and significant coefficient on "ask for antibiotics". This will imply that provider dispensing of antibiotics is sensitive to patient preferences. We expect the coefficient on "assigned ORS supply" to be positive and significant which will imply that providing ORS to providers increases ORS dispensing and that lack of availability of ORS at the clinic could be an important barrier.

Table 6. Impact of patient preferences and ORS supply on treatment for child diarrhea (regression results from equation 1)				
	(1)	(2)	(3)	(4)
	ORS dispensed or prescribed		Antibiotics dispensed or prescribed	
Ask for ORS				
Ask for antibiotics				
Assigned ORS supply				
Severe case				
Observations				
R-squared				
SP fixed-effects	Yes	Yes	Yes	Yes
Selected Covariates	No	Yes	No	Yes

Notes: This table will present coefficients from 4 regressions using equation 1.

Regression results for equation 4 (financial incentives)

We will present regression results for equation 2 in Table 7. The outcomes for this table are only whether treatments were "dispensed or prescribed" because SPs in the no incentive arm will only request a recommendation. This table will also include coefficients from regressions that interact "no incentive" with whether the provider dispenses medication directly from their clinic. We expect that the coefficient on no incentive will be negative when the interaction term is not included. With the interaction term included we expect the no incentive term to be close to zero and insignificant and the interaction term to be negative and significant (i.e., financial incentives are only relevant when providers are selling their medication). We expect that the interaction term in columns 2 and 4 will be larger magnitude than the "no Incentive" coefficient in columns 1 and 3, which would mean that the effect of removing financial incentives is driven primarily by providers who dispense their own medication.

Table 7. Impact of financial incentives on treatment for child diarrhea (regression results from equation 2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ORS dispensed or prescribed				Antibiotics dispensed or prescribed			
No Incentive								
Assigned ORS supply								
Dispense meds								
No Incentive X dispense meds								
Severe case								
Observations								
R-squared								
SP Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selected Covariates	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Columns 1 and 3 are from equation 2 and columns 2 and 4 included interaction terms for whether the provider dispensed medications.

Regression results for equations 5 and 6 (ORS availability at the clinic)

The coefficient on assigned ORS supply in table 6 represents the intention to treat effect of the ORS supply intervention. However, it does not represent the effect of ORS being available on site when the SP made the visits; providers not assigned supply could have ORS available and providers assigned supply could have sold out or gave it way prior to the visit. Our 2SLS instrumental variables approach will estimate the impact of ORS availability at the time of the SP visit. Column one reflect the first stage and estimates the impact of being assigned ORS supply on ORS availability at the time of the visit. The second stage regressions in columns 2-5 represent the effect of ORS availability at the time of the visit on the treatment outcomes. We expect the coefficient on "assigned ORS supply" to be positive in column 1 and the coefficients on "ORS available at clinic" to be positive when assess ORS and negative when assessing antibiotics.

Table 8. Impact of stock-outs on treatment for child diarrhea (2SLS results from equations 5 and 6)					
	(1)	(2)	(3)	(4)	(5)
	ORS available at clinic (first stage)	ORS dispensed (second stage)	ORS dispensed or prescribed (second stage)	Antibiotics Dispensed (second stage)	Antibiotics dispensed or prescribed (second stage)
Assigned ORS supply					
ORS available at clinic					
Ask for ORS					
Ask for antibiotics					
Severe case					
Observations					
R-squared					
SP Fixed-effects	Yes	Yes	Yes	Yes	Yes
Notes: Column 1 is the first stage from equation 3 with ORS availability at clinic predicted by whether the provider was assigned to receive free ORS supply. The second stage in columns 2-5 estimates the effect of ORS availability at the clinic.					

Regression results for equation 3 (interaction of supply and preferences)

Table 6 presents results for equation 5, which estimates heterogeneity in the effect of patient preferences based on whether the providers was given free ORS supply. We expect that requesting ORS will have a stronger effect among providers who were given ORS to dispense.

Table 9. Interaction between ORS supply availability and patient preferences				
	(1)	(2)	(3)	(4)
	ORS dispensed	ORS dispensed or prescribed	Antibiotics dispensed	Antibiotics dispensed or prescribed
Ask for ORS				
Ask for antibiotics				
Assigned ORS supply				
Ask for ORS X Supply				
Ask for antibiotics X Supply				
Severe case				
Observations				
R-squared				
SP Fixed-effects	Yes	Yes	Yes	Yes
Notes: This table interacts ORS supply and patient preferences				

Contribution of each mechanisms

Table 10 will present the parameters from the household and provider survey that we will use to bin patients and providers into the different categories of patient type. Table 11 will present the results of equations 6 through 9 to demonstrate the extent to which patient preferences, financial incentives, and ORS availability at the clinic contribute to inappropriate prescribing for child diarrhea.

Table 10. Parameters for simulation

	(1)
	Share of caretakers
Request antibiotics	
Request ORS	
Let provider decide	
	Share of providers
Dispense medication	
Higher profit from antibiotics	
ORS not available on site	
Notes:	

Table 11. Contribution of different mechanisms

	(1)	(2)
	Predicted share of cases receiving ORS	Predicted share of cases receiving antibiotics
Status quo		
Patient Preferences		
If share of patients requesting antibiotics decreased by 50%		
If all patients request ORS		
If all patients listen to provider		
Financial Incentives		
If there were no financial incentives		
Availability or ORS at facility		
If all providers had ORS available		
If ORS availability increased by 50%		
Notes:		

References

1. Black RE, Cousens S, Johnson HL, et al. Global, regional, and national causes of child mortality in 2008: a systematic analysis. *The Lancet* 2010; **375**(9730): 1969-87.

2. Cash RA, Nalin DR, Rochat R, Reller LB, Haque ZA, Mizanur Rahman ASM. A Clinical Trial of Oral Therapy in a Rural Cholera-Treatment Center. *The American Journal of Tropical Medicine and Hygiene* 1970; **19**(4): 653-6.

3. Pierce NF, Sack RB, Mitra RC, et al. Replacement of water and electrolyte losses in cholera by an oral glucose-electrolyte solution. *Annals of internal medicine* 1969; **70**(6): 1173-81.

4. Santosham M. Oral Rehydration Therapy of Infantile Diarrhea A Controlled Study of Well-Nourished Children Hospitalized in the United States and Panama. *The New England journal of medicine* 1982; **306**(18): 1070-6.

5. Spandorfer PR, Alessandrini EA, Joffe MD, Localio R, Shaw KN. Oral Versus Intravenous Rehydration of Moderately Dehydrated Children: A Randomized, Controlled Trial. *Pediatrics* 2005; **115**(2): 295-301.

6. Munos MK, Walker CLF, Black RE. The effect of oral rehydration solution and recommended home fluids on diarrhoea mortality. *International Journal of Epidemiology* 2010; **39**(suppl 1): i75-i87.

7. Victora CG, Bryce J, Fontaine O, Monasch R. Reducing deaths from diarrhoea through oral rehydration therapy. Geneva, Switzerland: World Health Organization, 2000.

8. Liu L, Johnson HL, Cousens S, et al. Global, regional, and national causes of child mortality: an updated systematic analysis for 2010 with time trends since 2000. *The Lancet* 2012; **379**(9832): 2151-61.

9. WHO, UNICEF. Diarrhoea: Why children are still dying and what can be done. Geneva: UNICEF/WHO, 2009.

10. Sreeramareddy CT, Low Y-P, Forsberg BC. Slow progress in diarrhea case management in low and middle income countries: evidence from cross-sectional national surveys, 1985–2012. *BMC pediatrics* 2017; **17**(1): 83.

11. DHS. India Demographic and Health Survey 2016, 2016.

12. Mohanan M, Vera-Hernández M, Das V, et al. The know-do gap in quality of health care for childhood diarrhea and pneumonia in rural India. *JAMA pediatrics* 2015; **169**(4): 349-57.

13. Kassegne S, Kays MB, Nzohabonayo J. Evaluation of a social marketing intervention promoting oral rehydration salts in Burundi. *BMC public health* 2011; **11**(1): 155.

14. Lenters LM, Das JK, Bhutta ZA. Systematic review of strategies to increase use of oral rehydration solution at the household level. *BMC Public Health* 2013; **13**(3): S28.

15. Rao KV, Mishra VK, Retherford RD. Knowledge and use of oral rehydration therapy for childhood diarrhoea in India: effects of exposure to mass media. 1998.
16. Wagner Z, Shah M, Sood N. Barriers to use of oral rehydration salts for child diarrhea in the private sector: evidence from India. *Journal of Tropical Pediatrics* 2014; **61**(1): 37-43.
17. Mohanan M, Babiarz KS, Goldhaber-Fiebert JD, Miller G, Vera-Hernández M. Effect of a large-scale social franchising and telemedicine program on childhood diarrhea and pneumonia outcomes in India. *Health Affairs* 2016; **35**(10): 1800-9.
18. Mohanan M, Giardili S, Das V, et al. Evaluation of a social franchising and telemedicine programme and the care provided for childhood diarrhoea and pneumonia, Bihar, India. *Bulletin of the World Health Organization* 2017; **95**(5): 343.
19. Friedman W, Woodman B, Chatterji M. Can mobile phone messages to drug sellers improve treatment of childhood diarrhoea?—A randomized controlled trial in Ghana. *Health policy and planning* 2015; **30**(suppl_1): i82-i92.
20. Basu S, Andrews J, Kishore S, Panjabi R, Stuckler D. Comparative performance of private and public healthcare systems in low-and middle-income countries: a systematic review. *PLoS medicine* 2012; **9**(6): e1001244.
21. Das J, Holla A, Mohpal A, Muralidharan K. Quality and Accountability in Health Care delivery: audit-study evidence from primary care in India. *American Economic Review* 2016; **106**(12): 3765-99.
22. Wagner Z, Asiimwe JB, Dow WH, Levine DI. The role of price and convenience in use of oral rehydration salts to treat child diarrhea: A cluster randomized trial in Uganda. *PLoS Medicine* 2018.
23. Doran T, Maurer KA, Ryan AM. Impact of provider incentives on quality and value of health care. *Annual review of public health* 2017; **38**: 449-65.
24. Basinga P, Gertler PJ, Binagwaho A, Soucat AL, Sturdy J, Vermeersch CM. Effect on maternal and child health services in Rwanda of payment to primary health-care providers for performance: an impact evaluation. *The Lancet* 2011; **377**(9775): 1421-8.
25. Gertler P, Giovagnoli P, Martinez S. Rewarding provider performance to enable a healthy start to life: evidence from Argentina's Plan Nacer: The World Bank; 2014.
26. Currie J, Lin W, Meng J. Addressing antibiotic abuse in China: An experimental audit study. *Journal of development economics* 2014; **110**: 39-51.
27. Currie J, Lin W, Zhang W. Patient knowledge and antibiotic abuse: Evidence from an audit study in China. *Journal of health economics* 2011; **30**(5): 933-49.
28. Dupas P, Miguel E. Impacts and determinants of health levels in low-income countries. Handbook of economic field experiments: Elsevier; 2017: 3-93.

29. Kremer M, Glennerster R. Improving Health in Developing Countries. *Handbook of Health Economics* 2011; **2**: 201-315.

30. Das J, Chowdhury A, Hussam R, Banerjee AV. The impact of training informal health care providers in India: A randomized controlled trial. *Science* 2016; **354**(6308): aaf7384.

31. Das J, Hammer J, Leonard K. The quality of medical advice in low-income countries. *The Journal of Economic Perspectives* 2008: 93-114.

32. Mohanan M, Goldhaber-Fiebert JD, Giardili S, Vera-Hernández M. Providers' knowledge of diagnosis and treatment of tuberculosis using vignettes: evidence from rural Bihar, India. *BMJ global health* 2016; **1**(4): e000155.

33. Iizuka T. Physician agency and adoption of generic pharmaceuticals. *American Economic Review* 2012; **102**(6): 2826-58.

34. Lopez C, Sautmann A, Schaner S. The Contribution of Patients and Providers to the Overuse of Prescription Drugs: National Bureau of Economic Research, 2018.

35. Lancet. Water With Sugar And Salt. *Lancet* 1978; **2**(8084): 300-1.

36. Wagner Z, Banerjee S, Mohanan M, Sood N. Does The Market Reward Quality? Evidence From India. *Under Review* 2018.

37. Sood N, Bendavid E, Mukherji A, Wagner Z, Nagpal S, Mullen P. Government health insurance for people below poverty line in India: quasi-experimental evaluation of insurance and health outcomes. *BMJ* 2014; **349**: g5114.

38. Sood N, Ugargol AP, Barnes K, Mahajan A. Applying appropriate-use criteria to cardiac revascularisation in India. *BMJ open* 2016a; **6**(3): e010345.

39. Sood N, Wagner Z. Impact of health insurance for tertiary care on postoperative outcomes and seeking care for symptoms: quasi-experimental evidence from Karnataka, India. *BMJ open* 2016b; **6**(1): e010512.

40. Sood N, Wagner Z. Social health insurance for the poor: lessons from a health insurance programme in Karnataka, India. *BMJ global health* 2018; **3**(1): e000582.

41. Center For Disease Dynamics and Policy. Global Antiotic Resistance Partnership: The State of the World’s Antibioitics 2015

.

42. Sood N, Wagner Z. Private sector provision of oral rehydration therapy for child diarrhea in Sub-Saharan Africa. *The American journal of tropical medicine and hygiene* 2014; **90**(5): 939-44.

43. USAID/UNICEF/WHO. Diarrhoea Treatment Guidelines: Including new recommendations for the use of ORS and zinc supplementation for clinic-based healthcare workers. Arlington, VA: USAID Micronutrient Program, 2005.

44. Das J, Holla A, Das V, Mohanan M, Tabak D, Chan B. In urban and rural India, a standardized patient study showed low levels of provider training and huge quality gaps. *Health affairs* 2012; **31**(12): 2774-84.

45. Rethans JJ, Gorter S, Bokken L, Morrison L. Unannounced standardised patients in real practice: a systematic literature review. *Medical education* 2007; **41**(6): 537-49.

46. Rethans J-J, Sturmans F, Drop R, Van der Vleuten C. Assessment of the performance of general practitioners by the use of standardized (simulated) patients. *Br J Gen Pract* 1991; **41**(344): 97-9.

47. Ada Kwan SB, and Benjamin Daniels, Jishnu Das, Veena Das, and Madhukar Pai. Using Standardized Patients to Measure Health Care Quality: A Manual and Toolkit For Projects in Low- and Middle-Income Countries, 2018.

48. Abaasa AM, Todd J, Ekoru K, et al. Good adherence to HAART and improved survival in a community HIV/AIDS treatment and care programme: the experience of The AIDS Support Organization (TASO), Kampala, Uganda. *BMC health services research* 2008; **8**: 241.

49. Manoj Mohanan, Veena Das, Diana Tabak, Brian Chan, Alaka Holla, Das J. Standardized Patients and the Measurement of Healthcare Quality: Field Guide, Manual, and Sample Instruments 2015.

50. Abadie A, Athey S, Imbens GW, Wooldridge J. When should you adjust standard errors for clustering?: National Bureau of Economic Research, 2017.