

## **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.<sup>1</sup> Nearly all of these deaths are the result of dehydration, which is cheaply preventable and treatable with the use of oral rehydration salts (ORS).<sup>2-6</sup> 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.<sup>7-9</sup> Despite these facts, only about a third of child diarrhea cases are treated with ORS globally<sup>10</sup> and only half of cases in India received ORS<sup>11</sup>.

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.<sup>11</sup> 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.<sup>12</sup> 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.<sup>16</sup> 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.<sup>13-15</sup> In 2016, over 85% of women in India had heard of ORS.<sup>11</sup> Finally, several studies that focused on increasing provider knowledge as a means of improving ORS use have been ineffective.<sup>17-19</sup> 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.<sup>20,21</sup> 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”)<sup>22</sup>, 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.<sup>23-25</sup> 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.<sup>26,27</sup>

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.<sup>16</sup>

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.<sup>13-15</sup> 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.<sup>28,29</sup> Our study will contribute in several ways. First, this literature predominantly 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<sup>12,30-32</sup> and

misaligned financial incentives.<sup>26,27,33</sup> 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).<sup>26,34</sup> 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,<sup>35</sup> is particularly limited.<sup>14</sup> 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.<sup>41</sup> 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.<sup>42</sup> 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.<sup>11</sup> 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 isolate the role of patient preferences from supply-side issues. **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 ask the provider for their 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 eliminates 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.

ORS dispensing/prescribing as outcome:

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**?*

Antibiotic dispensing/prescription as outcome:

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 preferences. 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.<sup>43</sup> 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).<sup>36</sup> 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 provides 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. Will compare the effects of SP preferences in the to the effect of different patient preferences presented to the provider in vignettes.

### **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.<sup>44-47</sup> 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.<sup>19,49</sup> 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 the what the fake patient will look like. If they describe a patient that fits our SP role, we will record this visits 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

**Table 3. ORS Supply Experimental Design**

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

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.<sup>16</sup> 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%).<sup>50</sup> 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).

We will distribute 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 sell at the market price. We will base supply quantities for each facility on diarrhea case load and provide enough ORS so that each case could receive two sachets of ORS (the recommended treatment quantity). 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 ensuring that ORS is stocked. 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 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 then sample all private providers who report treating cases of diarrhea in each town we visit. We will continue this process until we enroll 2000 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 - 2,000 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 their preferences for providers
  - a. This will be used to assess which provider characteristics patients value the most (technical quality, interpersonal quality, price, 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 of 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 match 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 SPs.

### **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).

**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.

<b>Summary of Data Sources</b>	
<b>Data Source</b>	<b>Key Outcome</b>
Household Surveys	Distribution of patient types 1, 2, and 3 (from Table 2) in real population
Provider Survey	Prevalence of Stock-Outs, provider knowledge
SP Visits	Dispensing of ORS and Antibiotics

Provider follow-up	ORS/antibiotic supply at time of SP visit
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## Primary Outcomes

The two primary outcomes will be whether the SP received ORS and whether the SP received an antibiotic. We will code a treatment as being received in two different ways. First, we will classify a treatment as being received if the provider *dispensed* the treatment to the SP. We will analyze our primary outcomes in this way when assessing the effect of patient preferences and the effect of ORS supply. Second, we will classify a treatment received if the provider *dispensed OR recommended* the treatment. In some cases, providers might recommend a treatment but not have it available to dispense that day. Moreover, type-4 SPs will only seek a recommendation, therefore our assessment of the effect of financial incentives will rely solely on provider recommendations and not SP acquisition. We will use this version when we analyze the effect of financial incentives or when we compare the effects across the three mechanisms (preferences, supply, and incentives).

## 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.<sup>6</sup> Second, ORS has been around for several decades and global use has been stagnant since 2005.<sup>10</sup> 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 targeting 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.<sup>12</sup> 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.

## 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.

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

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 severe) rather than case 1 (less severe). 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  $\beta_1$  and  $\beta_2$  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.<sup>50</sup>

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

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

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

Where  $\beta_5$  and  $\beta_6$  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.  $\beta_5$  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  $\beta_6$  will be negative in equation 3)

#### *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:

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

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,  $\beta_1$ , 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?
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 those that were not. This is estimated with  $\beta_4$  from equation 1. 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 vs. not 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:

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

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

In equation 5,  $Stock_i$  indicates whether provider  $i$  had ORS in stock during the visit from the SP. 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  $\lambda_1$  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  $\beta_4$  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.

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 and that ORS supply will have a larger effect in rural areas.
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)
3. *Whether provider dispenses ORS at baseline*: 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. *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.

5. *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.
6. *Qualifications of the provider:* we expect that providers with higher qualifications will be less responsive to patient preferences.

*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 stock-outs 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  $\beta_0$  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* term omitted). The  $\beta_1$  and  $\beta_2$  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 patient exit interviews. 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  $\lambda$  caretakers switch to requesting ORS instead of requesting antibiotics:*

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

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  $\lambda$ , 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  $\lambda$  and the share of patients that are type-2 decreased by  $\lambda$ .

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

	Patient Type		
	Type-1	Type-2	Type-3
Pr(ORS)	$\beta_0 + \beta_1$	$\beta_0 + \beta_2$	$\beta_0$
Share of Population	sT1	sT2	sT3

$\beta$  parameters estimated from equations 1 (with Case2 and Supply terms omitted)  
Share parameters estimated through client exit interviews  
T = Type; s = share

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  $\lambda$  values and compare to effect sizes of studies that evaluate interventions aimed at increasing ORS use.<sup>14</sup>

To estimate the total contribution of patients requesting antibiotics on underprescribing of ORS and overprescribing of antibiotics at the population level, we will set  $\lambda$  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.

**Interventions to decrease the financial incentive of providing ORS alternatives:**  $\beta_1$  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  $\lambda$ :*

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

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  $\lambda$ . If we set  $\lambda$  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.

### 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 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)	$\beta_0 + \beta_1$	$\beta_0$
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

	Patient Preferences				(5)
	(1)	(2)	(3)	(4)	
	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
<i>Treatments dispensed</i>				
ORS				
Antibiotics				
Zinc				
ORS + Zinc				
ORS and no antibiotics				
ORS+zinc and no antibiotics				
Total number of treatments				
<i>Treatments dispensed or prescribed</i>				
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
<i>Treatments dispensed</i>		
ORS		
Antibiotics		
Zinc		
ORS + Zinc		
ORS and no antibiotics		
ORS+zinc and no antibiotics		
Total number of treatments		
<i>Treatments dispensed or prescribed</i>		
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.

	(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				
Severe case				
Observations				
R-squared				
SP fixed-effects	Yes	Yes	Yes	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)
	ORS dispensed or prescribed	ORS dispensed or prescribed	Antibiotics 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

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 away 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.

	(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.

	(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
<i>Status quo</i>		
<i>Patient Preferences</i>		
If share of patients requesting antibiotics decreased by 50%		
If all patients request ORS		
If all patients listen to provider		
<i>Financial Incentives</i>		
If there were no financial incentives		
<i>Availability or ORS at facility</i>		
If all providers had ORS available		
If ORS availability increased by 50%		
Notes:		

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