To Charge or Not to Charge: Evidence from a Health Products Experiment in Uganda

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Abstract

In a field experiment in Uganda, a free distribution of three health products lowers subsequent demand relative to a sale distribution. This contrasts with work on insecticide-treated bed nets, highlighting the importance of product characteristics in determining pricing policy. We put forward a model to illustrate the potential tension between two of these important factors, learning and anchoring, and then test this model with three products selected specifically for their variation in the scope for learning. We find the rank order of percentage change of shifts in demand matches theoretical predictions, although the differences are not statistically significant, and only two of three pairwise comparisons match when the reductions are specified in percent terms. These results highlight the importance of understanding pricing policy with respect to product, market, and household characteristics.

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1 Introduction

A long literature in marketing, psychology, and economics investigates how prices may affect demand through channels other than the budget constraint. The reference price literature shows that price histories or even arbitrary prices can directly influence potential buyers' willingness to pay for a product.[1] The empirical literature from marketing and psychology, built largely on classroom and lab experiments as well as supermarket scanner data, finds a large role for price anchors.[2] All else equal, a lower price today makes the price tomorrow seem higher.

In contrast, a number of recent randomized field studies, particular those related to the hotly contested issue of pricing health goods in low-income countries, find little evidence for such non-budget-constraint effects of prices on demand and usage.[3] This has produced a loose consensus around the policy of free distribution for a variety of basic health products (J-PAL, 2011). Reconciling these two seemingly divergent sets of findings has profound implications for the distribution of health products but also for agriculture, where government policies often include free or subsidized inputs.

[1]In psychology, there is a long history of studying the effect of reference points in absolute judgments. See, for example, Sherif et al. (1958). Doob et al. (1969) proposed a theory of cognitive dissonance to explain results from a series of field experiments demonstrating that low introductory prices of new brands generated lower sales in the long run than introducing the product at its normal selling price. A range of studies have demonstrated anchoring effects in estimation tasks (e.g., Tversky and Kahneman 1974; Jacowitz and Kahneman 1995; Chapman and Johnson 1999; Epley and Gilovich 2001). The role of such anchors in the formulation of individuals' values has since received considerable attention (Ariely et al., 2003; Mazar et al., 2013), although the robustness of such non-budget-constraint effects of prices on demand has recently been called into question (Fudenberg et al., 2012; Maniadis et al., 2014).

[2]Classroom and lab experimental examples include Winer (1986); Kalwani and Yim (1992); Raghubir and Corfman (1999); Adaval and Monroe (2002); Kopalle and Lindsey-Mullikin (2003); Anderson and Simester (2004); Adaval and Wyer Jr (2011) and Rao and Monroe (1989). Mayhew and Winer (1992), Dekimpe et al. (1998), and Kalyanaram and Little (1994) demonstrate reference price effects with scanner data. Nunes and Boatwright (2004) provide evidence for the role of incidental prices in a range of settings, and Simonsohn and Loewenstein (2006) demonstrate behavior consistent with price anchors in the apartment rental decisions of individuals moving to new cities.

[3]Most directly related are Cohen and Dupas (2010) and Dupas (2014) in the context of insecticide-treated bed nets and Ashraf et al. (2010) in the context of home water purification. Heffetz and Shayo (2009) also find no evidence of large non-budget-constraint effects of prices on food purchases in either a lab or field experiment.

It is unlikely that a single pricing policy—for example, free distribution—is optimal for an entire class of goods. On the other hand, answering the question "to charge or not to charge" should not require case-by-case experimentation with no room for generalization. Rather, the ultimate aim is to have an empirically validated model that maps from product, market and household characteristics to an optimal pricing and distribution policy.

To make progress towards this goal, we argue theoretically and show empirically that differences in the scope for learning about the value of an experience good—for which utility is revealed through use—are likely important. To understand the core intuition, note that reducing short-term prices has two distinct effects. On one hand, lower prices, including "free trial" periods, increase demand during the low-price period. In addition to any direct benefit from this, those who purchase the product have an opportunity to learn directly about the product's effectiveness. Depending on prices and individuals' prior beliefs about the value of the product, this learning effect can either increase or decrease subsequent demand. On the other hand, lower current prices may serve as reference points or "anchors" that affect subsequent demand independently of intrinsic value.

Using a theoretical framework built on this intuition, we designed a field experiment in northern Uganda where three curative health products—Panadol, Elyzole, and Zinkid—were distributed door-to-door either for free or for sale at market prices. All three products are quite different from ITNs, the main product for which this question has been studied. They are curative rather than preventive, consumable rather than durable, and unlikely to have meaningful income effects.[4] In stark contrast to the existing literature, we find that across all three products prior free distributions reduce subsequent demand.

[4]The use of ITNs reduces the incidence of malaria and may thereby increase households' income and, in turn, future demand for additional ITNs (see footnote 27 of Dupas (2014) for more discussion). In our context, as discussed in Section 4, we do not believe any income effects would be substantial. We also would expect income effects to lead to increases in demand from free distribution, which is not what we find. ITNs are a key element in vector control and hence have significant positive externalities. There is also significant scope for learning about the proper use and effectiveness of bed nets.

We can rule out several alternative mechanisms for the difference, including the mechanical effect of having more of the product on hand if it had been previously distributed for free. Households' qualitative responses also support our empirical conclusions: those who received free distribution are more likely to report that they do not want to purchase the product because they or someone in their community had received it for free in the past.

Among the three products, Panadol, a pain reliever widely known to consumers, provides a pure test of anchoring. It is free from most potentially conflating effects of a free distribution on subsequent demand: there are no positive externalities, little to no scope for learning, and small if any income effects. Thus the main mechanism through which current prices can affect future demand is negative anchoring effects.[5] Indeed we find that a free distribution of reduces subsequent demand, consistent with models of reference-dependent preferences (Kőszegi and Rabin, 2006; Mazar et al., 2013; Heidhues and Kőszegi, 2014) where comparison effects dominate. The share of households purchasing Panadol from an unrelated, for-profit firm is 12 percentage points lower ten weeks after free distributions than after sales at market prices.

For health products in low-income countries, where free or heavily subsidized distribution is a common but controversial practice, there is a natural tension between price anchors and the potential for learning about a product through use. Health products are a canonical experience good, where in addition to any aggregate uncertainty relating to the product there may be significant variation in the benefits or side effects across individuals. Moreover, in low-income countries, the quality of medical advice may be low (Das et al., 2008) so experiential learning may be especially important for long-run demand.

In order to explore this tension, we study two other products that, unlike Panadol, have

[5] Panadol is not unique in its ability to isolate potential anchoring effects. One could use any well-known product with potential for repeat purchase and free from confounding effects (e.g., croissants). Panadol has the advantage of sharing characteristics common to the class of health goods, such as being distributed through drug shops and health centers.

scope for learning. Experience with Elyzole, a moderately well-known deworming drug, likely produces negative learning due to unpleasant side effects. In contrast, experience with Zinkid, an improved but largely unknown treatment for childhood diarrhea that was recently recommended by the World Health Organization at the time of our study, likely produces positive learning.

For both products, prior free distribution reduces demand. As predicted by the theory, the relative reduction in percentage point terms is larger when there was scope for negative learning (Elyzole) and less negative when there was scope for positive learning (Zinkid). In the latter case, the reduction in demand caused by a free distribution is not statistically distinguishable from zero. The pattern is consistent with the theoretical prediction that positive learning can offset negative demand effects from price anchoring; however, we note that none of the differences across products are statistically significant at conventional levels. Furthermore, only two of the three pairwise comparisons conform to the theoretical predictions when the reductions are specified in percent terms rather than percentage points. The percent reduction in demand for Zinkid, with its relatively low base, is slightly larger than that for Panadol, which is purchased by the large majority of households. While firms may be more interested in percents, which relate directly to elasticity and thus profit calculations, we focus on percentage point changes as this is typically the policy-relevant object. For example, measurement of the Millennium Development Goals focuses extensively on the proportion of populations covered by crucial health services (UNDP, 2009). It is also the norm in the experimental literature on health product pricing in developing countries (see Cohen and Dupas, 2010; Ashraf et al., 2010; Dupas, 2014; Tarozzi et al., 2014).

To test auxiliary hypotheses about the mechanisms through which price anchors may affect subsequent demand, we also experimentally varied the identity of the organization distributing the products in the first wave between either a for-profit pharmaceutical company or a non-profit NGO. For-profit companies often offer free samples or steep introductory discounts with no expectation that these will continue. Therefore, we hypothesized that free distribution by a for-profit firm would shift price reference points less than distribution by an NGO from whom individuals could reasonably expect future free distributions. Contrary to our hypothesis, we find no evidence of a differential effect; free distribution by either type of organization reduces demand.

However, distributor identity does matter for the contemporaneous sale of the relatively unknown product. Households are 14 percentage points (50 percent) more likely to purchase Zinkid from the non-profit than from the for-profit firm selling at the same price and providing the same product information. We find no difference for the more well-known products. The finding that NGOs are more effective at stimulating demand for unknown products has important policy implications but was not one of our ex ante hypotheses. Furthermore, this difference does not persist: there is no discernible difference in the subsequent purchase decisions from an unrelated, for-profit firm between those who were originally offered the product by the NGO or for-profit marketers.

Finally, we find no evidence that the price anchoring effect of free distributions for one product spills over to the demand for other health products. There is no discernible effect of having received a product for free in the first wave on the demand for Aquasafe, a new product offered only in second wave. However, we note that confidence intervals for the cross-product effect are large.

We find negative effects on subsequent demand from prior free distribution for all three products tested, but we stress that there is no generic answer to the question of whether to charge or not to charge. One must examine specific product, market and household characteristics to form proper policy implications. In aiming to illustrate the tension between learning and reference-dependent preferences, we abstract from a number of potentially important factors such as income effects, externalities, and habit formation. We return to these in discussing the generalizability of our results in Section 4. Furthermore, while context and product characteristics may differ greatly and governments, firms and other organizations may have different objective functions when distributing products, our results demonstrate that the tension between price anchors and learning is likely to be a critical factor in many cases.

2 Experimental design & data

2.1 Experimental design

Setting and sampling. We conducted our experiment in Gulu District in northern Uganda.[6] We selected 120 villages for the study and from each of these villages randomly selected approximately 50 households from the household list kept by the village chief.[7] Each village was divided geographically into three groups and each group assigned to a marketer.[8]

[6] We selected the Gulu District in order to conduct this study in conjunction with a methodological study that compared the accuracy of data collected by professional surveyors hired and trained by Innovations for Poverty Action to data collected by "community knowledge workers" (CKWs), local community members hired by Grameen Foundation to both disseminate and collect information. The Gulu District was destabilized by an insurgency from 1987 until 2006. In the wake of the insurgency, the area received a large amount of NGO and government attention. Many NGOs were active in reconstruction and service provision, including providing free health care and health products. Relative to other regions in Uganda, the Gulu District is likely at the upper end of the distribution in terms of prior exposure to free or heavily-subsidized distributions of health goods. We believe this represents a conservative test for the effect of past prices on current demand based on our expectation that prior exposure to free distributions would mute the effect of any single subsequent distribution; however, demand could be particularly sensitive in an environment with high NGO activity.

[7] Of these 120 villages, 72 were participating in the contemporaneous methodological study. These villages were selected based on their availability of certain administrative data. The remaining 48 villages were selected randomly from an administrative government list of villages in Gulu. The number of households drawn in each village depended on the number of respondents from the parallel study, which in turn was determined by the number of households for which institutional data were available. The sample of the parallel study consisted of names of recipients for NGO and government services, including free bed nets, free seedlings, and tarpaulins, as well as clients of a local bank. All 859 such individuals were included in the sample, and the remaining households were randomly selected from household lists maintained by local village leaders in order to arrive at a sample of approximately 50 households per village. In Uganda, the village chief is referred to as Local Council 1 Chairperson ("LC1").

[8] Grouping was done based on logistical ease. Groups were not always of equal size, but rather defined so as to minimize distances between respondents for each marketer.

First wave of marketing. The first wave of marketing (Wave 1), conducted in October-November 2011, employed a two-level clustered randomization design, with randomization both at the village and individual level. First, villages were randomly assigned to one of four treatment groups in a two-by-two design.[9] The first treatment dimension was the price of the product, either free ("Free") or sold ("Sale"). The second dimension was the type of distributing organization: either a not-for-profit, non-governmental organization ("NGO") or a for-profit business ("For-Profit"). Thirty villages were assigned to each of the four treatment cells. Table 1 illustrates balance across our village treatment assignments.

Then, at the household level, we randomly assigned one of three products to be offered to each household: Panadol (paracetamol, a painkiller), Elyzole (albendazole, a deworming medication), and a combination pack of Restors and Zinkid (oral rehydration salts, "ORS" and zinc supplements, the World Health Organization's recommended treatment for childhood diarrhea). For the Sale treatment group, we used the same price for the entire study. We set the price for the Sale group to be slightly above the average perceived price (from a price perception survey, see below) in order to minimize the chance that respondents were purchasing only in order to resell and to approximate a market price (i.e., the perceived price plus a small add-on for the convenience of buying at one's home).[10,11]

[9] Village assignment to treatment was block randomized according to two variables. The first, price environment, included information about pricing and drug availability with three possible categories: (1) no drug outlets or none of our drugs; (2) no prices above the median or distributed for free; and (3) at least one price above the median. The second, remoteness, also had three categories: (1) easy to travel and close to health center; (2) difficult travel or far from health center; and (3) difficult travel and far from health center.

[10] Note we randomized the presence of free versus sale distribution, and NGO versus for-profit, at the village level, whereas the exact product received we randomized at the individual level. Thus our estimates are not biased from spillovers if the information flow is about the presence of an organization giving out free health products. The correct interpretation of our estimates includes both a the direct effect of the treatment on a household's later behavior and a potential reinforcement effect (those around them also received the same treatment and, through conversations and sharing of information, reinforced any effect). We are estimating the combined effect, which is also the policy relevant parameter given the typical practice of community-level distribution of health products. However, given that the exact product distributed was randomized at the household level, giving out a particular health product for free may have cross-product spillovers. While this could bias product-specific estimates, based on results reported below on cross-product effects, we believe this is not an important risk.

[11] In earlier circulated versions of this paper, we referred to this as selling above the market price, but we

In order to maximize the likelihood that individuals perceived the various marketing and sales interactions as natural rather than experimental artifacts, we partnered with real Ugandan organizations involved in the provision of health products. For the NGO treatment group, we worked with the Uganda Health Marketing Group ("UHMG"), a large Kampala-based NGO largely funded by USAID and focused on the distribution and promotion of health products. For the For-Profit distribution, we worked with Star Pharmaceuticals Ltd ("Star"), a large, Kampala-based company that imports, distributes and markets medicines and other products for sale throughout Uganda. Although the marketers were employed by UHMG and Star, we recruited, trained and monitored the marketers using the same protocols for both NGO and For-Profit distribution. Marketers wore branded t-shirts and displayed ID-cards from the relevant partner organization. The field marketers were all locally recruited, reducing communication barriers.

To mitigate potential liquidity constraints in the Sale treatment arm, several days beforehand the marketers distributed flyers throughout the village to announce the upcoming marketing visit. The aim was to reduce short-term liquidity constraints. In order to minimize potential for differential response rates, a similar flyer was distributed in the Free treatment arm announcing a distribution but not detailing whether products would be free or sold.[12]

have changed the language to refer to it as perceived price for two reasons. First, because there are no posted prices, most individuals' set their final prices through a process of bargaining. Fitzpatrick (2014) finds that 48 percent of customers at informal drug shops successful bargain over the price of anti-malarial medicines. Second, our door-to-door distribution also builds in transport and convenience, which we would expect to influence households' perception of how competitive our prices are relative to other alternatives. The prices set in the first wave were as follows: Panadol: UGX 500 ($0.20) for a strip of ten tablets, Elyzole: UGX 1,800 ($0.71) for a pack of six tablets, Restors/Zinkid combination pack: UGX 2,000 ($0.79) for one sachet of Restors and ten tablets of Zinkid.

[12]The flyers differed slightly by referring to an "upcoming distribution" in the Free treatment villages and an upcoming "sale at a good price" in the sale villages. This may have induced different average rates for entering into the Wave 1 sample frame between the Sale and Free treatments (65.4% versus 70.5%, respectively). As shown in Panel A of Appendix Table A1, the differential entry rate is larger for households assigned Panadol. However, the flyers were distributed widely in the village and made no mention of the product that was going to be offered, which was randomized at the household level and only revealed to households once they entered the sample frame. We therefore conjecture that the imbalance for Panadol

Throughout the study we attempted to adhere to a natural marketing process, typical in this region. We wanted to avoid marketing procedures that deviated considerably from normal operating practices of NGOs or firms, so that the observed reactions of respondents would be more natural. In particular, we expected that returning on several consecutive days to a remote village to search for a specific respondent by name would be perceived as atypical behavior for an NGO or ostensibly profit-maximizing firm with the aim of sustainable product delivery. This in turn could generate experimenter effects and mask the true effect of price anchors. While this methodological choice gives us greater confidence that our findings accurately reflect the effect of free distributions in non-experimental settings, it is not without costs. Out of the original 5,707 households identified to be in the study, 3,879 were found in the first wave of marketing. This is a lower level of entrance into the sample frame than often found in studies in developing country studies. As discussed more fully below, this pattern reappears when looking at attrition in our second wave. In each attempt to locate specific respondents we found approximately 75 percent of targeted individuals.

Marketers delivered sales pitches specific to each product, price treatment (free or sale) and entity (NGO or for-profit). A pharmacist trained the marketers on how to explain usage and dosage guidelines, and other such questions about the products.[13] See Appendix B.1 and B.2 for details on the marketing scripts.[14]

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was due to bad luck and not selection on unobserved willingness-to-pay for the product. Nevertheless, in an extreme bounding exercise that assumes differential selection into the study is perfectly predicted by willingness-to-pay such that those who were not found would never purchase the product, the results on Panadol would be null, whereas those for Elyzole and Zinkid would remain unchanged.

[13] Marketers gave respondents information on dosage, storage and recommended use of the respective product both verbally and in writing in Acholi, the local language. This information was based on the instruction sheet of the drug and formulated in consultation with a pharmacist and board member of the Ugandan National Drug Authority.

[14] The pamphlets distributed to households ahead of time stated that at your door there will either be a "distribution of health products at your door on [...], be prepared!" or "health products for sale at your door on [...], be prepared!". However, the in-person script, for the Sale treatment by an NGO, explained the sale price by saying "pay a small amount to share" in the cost, whereas the sale script for the for-profit said "at great prices". Although there are merits to both, we suggest using the phrase "at great prices", or something

In Wave 1, we offered one unit of the assigned product to households in the Free treatment arm and five units to those in the Sale treatment.[15] Prices were non-negotiable. Once this transaction had been completed, marketers administered a questionnaire to respondents in the Sale treatment group about why they decided to buy or not to buy and who might use the product.[16] In all cases, marketers had only one day to reach all respondents in each village. Marketing was not continued on a second day in order to reduce the possibility of spillovers of information or expectations across respondents.

The three products were chosen deliberately to capture a range of potential learning effects that could influence purchase decisions. Panadol is a common pain reliever and was by far the most well-known product. Most respondents were likely to have been familiar with the product (95 percent) although only few with the brand itself (10 percent). The generic version of Panadol is widely available in most drug shops, and we expect little scope for learning. Elyzole was less well-known as a brand, but other brands of deworming medication with the same active ingredient (albendazole) have been widely distributed. Based on the relative salience of immediate side-effects, we expected that any learning effects would be negative despite potential for long-run benefits (Miguel and Kremer, 2004). Zinkid was sold in combination with Restors, an oral-rehydration salt, following clinical recommendations (World Health Organization, 2005). While Restors was a new brand,[17] the generic version (ORS) was widely used, recognized and freely available from health

similar, for both NGO and for-profit entities for any replications or extensions of this, as the NGO wording we used more strongly implies a sale at lower than market prices. The phrase "at great prices" is common for marketing by for-profit entities such as UHMG and Star.

[15]One unit corresponds to the smallest amount of each product that could be sold separately. For Panadol this was 10 tablets, for Elyzole this was 6 tablets, for Restors/Zinkid this was 1 sachet of Restors and 10 tablets of Zinkid, and for Aquasafe this was 8 tablets. Prices are given above. Only 2.5 percent of households in the Sale treatment purchased five units, suggesting that the cap on the quantity of units for sale was only rarely, if ever, binding.

[16]This survey was not conducted in the Free group in order to keep the interaction more natural.

[17]Restors is an ORS formulation with lower osmolarity which was recommended by the WHO in 2006 (WHO 2006). The lower osmolarity results in lower stool output by children with diarrhea, as compared to the old formulation Hahn et al. (2002).

centers.[18] However, the importance of zinc supplements in combating diarrhea had only recently been established in the global health literature.[19] As such, Zinkid represents a new brand and product for which we expect there to be scope for positive learning. In a study carried out with Zinkid users by our partner the Ugandan Health Marketing Group in 2012, 93 percent of zinc users believed that the product was an effective treatment for diarrhea, citing a quick end to diarrhea and fast recovery by the child as primary reasons for this belief.[20] Table 2 presents descriptive results from the price perception and product awareness survey.

Second wave of marketing. We conducted the second wave of marketing (Wave 2) on average ten weeks after Wave 1, in December of 2011.[21] The sole purpose of Wave 2 was to get an outcome measure of respondents' willingness to pay for health goods. In order to avoid reputation effects from the first stage, we partnered with a different for-profit firm, Surgipharm Uganda Ltd ("Surgipharm"). Again, marketers were employed by the partner, but recruited, trained and monitored by the study team. In order to reduce association between the two waves, we changed the wording of all scripts without significantly affecting the content. In order to reduce the probability that respondents associated Wave 2 with Wave 1, we also assigned marketers to villages such that individual marketers did not visit

[18]One concern about bundling ORS and zinc is that children and caregivers often cite the bad taste of ORS as a reason for not using it (Freedman et al., 2010). However, ORS is a widely known therapy recommended by the WHO since 1980 (da Cunha and Cash, 1989). If any learning occurs with ORS in our sample it occurs because the formulation we distributed had lower osmolarity and therefore may have had a slightly improved taste and because the low osmolarity formulation results in reduced stool output.

[19]Zinc became part of the WHO guidelines for the treatment of diarrhea in 2006. Larson et al. (2009) find that use of zinc supplements in rural areas lags adoption among urban and high income individuals. Evidence from studies in Tanzania and Benin suggest that while the prescription of zinc for childhood diarrhea is increasing, the majority of diarrhea cases are not yet treated with zinc (Sanders et al., 2013).

[20]The three products also differ in terms of who would be the target user, which could affect the scope for learning. The type of Panadol used was aimed at adults only; children under 12 were not allowed to use it. Although Elyzole could be used by people of any age (except babies), parasitic infestations are most acute amongst children. Zinkid was a product specifically aimed at children, with a target age group of six months to five years.

[21]The minimum number of weeks between marketing waves was 6, the maximum 12 weeks, and the median is 10 weeks. Timing varied for logistical reasons, such as weather and holidays. We do not find any evidence that observed effects are correlated with differences in the number of days between waves.

the same village twice. While there may be time trends in the demand for health products, we do not believe there is any reason to expect seasonal fluctuations in demand to vary according to treatment status.[22]

As a further test of the scope of price anchoring effects, we investigate whether having received any product for free affects demand for other health products. We therefore assigned 25 percent of households to be offered a fourth product not offered in Wave 1, Aquasafe, a product designed for home water purification. The concept of water purification was well-known and understood; however, although Aquasafe is one of the two leading brands for water purification, the name itself was not well known by respondents (only 16 percent recognized the brand, as shown in Table 2). Since no learning about specific product characteristics takes place across products, the cross-product test allows us to assess whether price anchoring will occur for broadly construed product categories, such as "health products".[23] In the second marketing wave, the only randomization was the household-level assignment of the product: 25 percent of households were marketed the new product, Aquasafe, and 75 percent the same product from Wave 1. Figure A1 summarizes the experimental design.

Attrition. In Wave 2, we found 2,887 of the 3,879 individuals treated in Wave 1. This attrition rate of 25.6% resulted from a deliberate methodological decision to adhere to a natural marketing process. As shown in Appendix Table A1, attrition between waves is uncorrelated with individual characteristics (other than gender), including whether or

[22]Panadol is a pain-killer that is used frequently to treat a variety of illnesses year-round, especially as it often means avoiding a visit to the health center. The Ugandan Ministry of Health suggests preventive deworming of children every three to six months, so we would expect participants to demand more deworming medication at the time of our second visit (Ministry of Health, Republic of Uganda, 2012). Childhood diarrhea is more common during the rainy season (Ahmed et al., 2008), therefore we might expect higher demand for Zinkid to treat diarrhea in Wave 1 when rains were more common.

[23]The mechanisms of any such cross-product effects could include beliefs about the general quality of products marketed in a particular way (i.e., door-to-door or by a for-profit entity) or categorical price judgments, whereby individuals judge utility of purchase by comparing price of product to endpoints or distributions within the product category. For discussions of the latter mechanism, see, for example, Alba et al. (1999) and Mazar et al. (2013).

not the subject received the product in Wave 1. See Panel B of Appendix Table A1 for details. Attrition is not correlated with assignment to the Free or Sale treatments. We found 74.7% and 74.2% of Wave 1 subjects, respectively (p-value: 0.856). Attrition is, however, marginally correlated with assignment to the NGO vs. for-profit treatments, where we found 76.5% vs. 72.3% of subjects, respectively (p-value: 0.110).

2.2 Data

Village and drug outlet data. Before Wave 1, we surveyed community leaders and drug outlets. We first asked the village chief about the number and type of drug outlets (including drug shops, clinics and hospitals) in each village, the distance (in time and kilometers) to the most popular and nearest facilities and any recent free distributions of health products. We then visited every drug outlet (including both private drug shop and local health clinics) in each village and asked about the price, availability and preferred brand for a list of common drugs. There were drug outlets in 64 of the 120 villages and, when a drug outlet was present, an average of 2.4 outlets per village. We used these data to determine the relevant "shop price" for the drugs we were offering, stratification, and to test for treatment effect heterogeneity.

Price perception survey. Immediately prior to offering the product, marketers administered a price perception survey to 50 percent of respondents in Wave 1. After introducing themselves, marketers showed respondents the two products *other than the one assigned to that individual* to avoid potential anchoring effects on the product about to be offered for sale or gift. After a brief description of the use of the product in general, respondents were asked about their familiarity with the product and brand. If they were familiar with the product, they were asked where they could purchase it and what price they would expect to pay. In Wave 1, we solicited price perceptions of the three goods distributed in the wave.

In Wave 2, individuals were asked only about the new product, Aquasafe.

Post marketing survey. In order to understand the mechanisms influencing purchase decisions, we conducted a short survey (Appendix C) of all individuals who were offered products for sale (those assigned to the Sale group in the Wave 1 and all individuals in Wave 2). The survey was designed to mimic traditional marketing research in order to ensure that participants' experience was natural. The survey asked respondents in an unprompted way to explain why they did or did not purchase the product.

Observational usage data from physical observation of packaging. During Wave 1, all respondents who had received a product, whether for free or purchased, were informed that that they had also been entered into a lottery. If selected, they would need to present the product packaging (blister packs) in order to claim their prize. It was clearly stated that the prize did not depend on how much of the product was used, only on whether they presented the blister packs. Six to eight weeks after Wave 1 (two to four weeks before Wave 2), surveyors made unannounced visits to a sample of 329 households that received a product in Wave 1 and recorded how many tablets were remaining in the blister packs.[24]

3 Theoretical framework

We put forward a model of households' decisions to purchase non-durable health products that includes both price anchoring and learning. With our focus on these elements, we abstract away from other potentially important issues, such as health externalities, learning

[24]Surveyors were given details about how many units of the product each respondent had received, and so were able to verify whether all packaging was present. Furthermore, all blister packs distributed by marketers in Wave 1 had been discretely marked so that they could be identified as packaging distributed by our marketers, rather than the same product obtained from elsewhere. Here we deviated from our overall strategy of "naturalness." In many design issues, we aimed to make the process as natural as possible from the participant's perspective, so that behavior would be less likely to shift because of Hawthorne, John Henry or mere measurement effects. In this instance we felt that acquiring some data on usage was important enough to deviate, but to roll it out in a promotional way so that it still was implemented under the pretense of a market introduction of goods. Those who did "win" the lottery (about 10%) do not behave differently in Wave 2.

from one's neighbors, expectations about product quality, knowledge of price distribution, risk aversion, and habit formation. While the mechanisms we describe are applicable to repeated purchase opportunities, the key features can be seen in a simple two-period, latent utility model. This set-up differs from typical settings in which experience goods are analyzed in that (1) rather than constrain the distributor to be a profit maximizer, we remain agnostic regarding its objective function and (2) similar to Dupas (2014), we enrich the latent utility framework to allow for gain-loss utility. Where required, additional derivations and proofs appear in Appendix A.

In each period, a household chooses to purchase a health product if and only if its expected utility from the product exceeds the utility cost. In any period t, a household i purchases the product if and only if

$$v_{it} \equiv E_{it}(v_i) > \varepsilon_{it} + a p_t + R(p_t - p_t^r), \tag{1}$$

where $E_{it}(v)$ is the expected value (v_i) of the product to household i at time t; ε_{it} is a normally-distributed, household- and time-specific preference shock with mean zero and variance σ_ε^2; p_t is the price at which the product is offered in period t; a is the marginal utility of income, which we normalize to 1; and $R(p_t - p_t^r)$ is the gain-loss utility from purchasing at price p_t relative to reference point p_t^r (Kőszegi and Rabin, 2006; Heidhues and Kőszegi, 2014). We specify that $p_t^r = p^r(p_{t-1}, d)$, that is, the reference point is a function of both the immediately preceding price and the identity of the distributor, d, which can be either an NGO (N) or a for-profit enterprise (F). We allow for any general form of gain-loss utility such that $R' \geq 0$ and $\partial p_t^r / \partial p_{t-1} > 0$. This simply implies that an increase in current prices will increase the future price reference point, and utility is increasing in this reference point as any realized future price represents a "better deal". Likewise, a decrease in current price implies the opposite. It will be convenient to define the *adjusted price* as $\tilde{p}_t = p_t + R\left(p_t - p_t^r\right)$, that is, the current price plus the gain-loss utility from purchasing at that price. For notation, if household i purchases the product in period t, $P_{it} = 1$; if she does not, $P_{it} = 0$. We denote by π_{it} the probability that household i purchases the product at time t, and by π_t the expected share of the population that purchases.

Households are heterogeneous and differ in their true value of the product, v_i, where $v_i = \bar{v} + \sigma_{iv}$. For analytical tractability, we assume that this true value is normally distributed, $v_i \sim N(\bar{v}, \sigma_v^2)$. In period 0, a share of the households, $\alpha_0 \in [0,1]$, is informed of their true values. The remaining households receive a signal of their value, $\tilde{v}_{it} = v_i + b + b_{it}$, where b captures the mean bias in the population and $b_{it} \sim N(0, \sigma_b^2)$.[25] Note that we are explicitly allowing for the possibility that the expected value of the product in the uninformed population may differ from the truth. If households tend to be optimistic about the value of a product, b will be positive; for pessimistic beliefs, b will be negative. For informed households, $v_{it} = v_i$, i.e., the true value. As in other literature on experience goods pricing (Bergemann and Välimäki, 2006), if a household receives the product, we assume they become perfectly informed about its value to them.

The share of individuals purchasing in period t can be expressed as follows:[26]

$$\pi_t \quad = \quad \alpha_t E\left(\pi_t | Informed\right) + (1-\alpha_t) E\left(\pi_t | Uninformed\right). \tag{2}$$

The expected share of informed individuals purchasing in any period can be calculated

[25]This is an alternative representation for the definition of pessimistic and optimistic customers used by Shapiro (1983).

[26]Note that this model implicitly assumes that individuals cannot store the product. They do not buy today with the intent of consuming in a subsequent period. This assumption is important. If individuals could store the product for later consumption, individuals who received the product for free in round 1 may carry over stock into round 2, mechanically reducing demand. In Section 4.3 we discuss the empirical support for the assumption and show that individuals in our experiment indeed do not appear to be storing the product for future consumption. We also assume, consistent with the work of Shapiro (1983), Milgrom and Roberts (1986), Tirole (1988) and Villas-Boas (2004), that consumers do not have an experimentation motive for purchases. Such experimentation is analyzed in Bergemann and Välimäki (1996, 2006) and would not substantively alter the predictions of this theoretical framework.

simply as:

$$
\begin{aligned}
E\left(\pi_t|Informed\right) &= Pr(v_i > \varepsilon_{it} + \tilde{p}_t) \\
&= Pr(\bar{v} + \sigma_{iv} - \varepsilon_{it} > \tilde{p}_t) \\
&= \Phi\left(\frac{\bar{v} - \tilde{p}_t}{\sigma_I}\right),
\end{aligned}
$$

where $\sigma_I^2 = \sigma_v^2 + \sigma_\varepsilon^2$. Similarly, the expected share of uninformed individuals purchasing in any period can be calculated as:

$$
\begin{aligned}
E\left(\pi_t|Uninformed\right) &= Pr(\tilde{v}_{it} > \varepsilon_{it} + \tilde{p}_t) \\
&= Pr(\bar{v} + \sigma_{iv} + b + b_{it} - \varepsilon_{it} > \tilde{p}_t) \\
&= \Phi\left(\frac{\bar{v} + b - \tilde{p}_t}{\sigma_U}\right),
\end{aligned}
$$

where $\sigma_U^2 = \sigma_v^2 + \sigma_b^2 + \sigma_\varepsilon^2$. This implies that there is more variation in the signal households receive about the true value of the product than in the underlying true value, and hence $\sigma_U^2 > \sigma_I^2$.[27]

The key predictions of the model are all derived from differentiating (2) with respect to the price in the preceding period, p_{t-1}. This leads to:

$$
\begin{aligned}
\frac{\partial \pi_2}{\partial p_1} &= \frac{\partial \alpha_2}{\partial p_1}\left[\Phi\left(\frac{\bar{v} - \tilde{p}_2}{\sigma_I}\right) - \Phi\left(\frac{\bar{v} + b - \tilde{p}_2}{\sigma_U}\right)\right] \\
&\quad - \frac{\partial R}{\partial p_1}\left[\frac{\alpha_2}{\sigma_I}\phi\left(\frac{\bar{v} - \tilde{p}_2}{\sigma_I}\right) + \frac{1-\alpha_2}{\sigma_U}\phi\left(\frac{\bar{v} + b - \tilde{p}_2}{\sigma_U}\right)\right].
\end{aligned}
\tag{3}
$$

The first term on the right-hand side of (3) is the information effect. It can be either positive

[27] While it is possible for uninformed priors to be tightly distributed around a common mean and posterior beliefs, informed by experience, to be more dispersed, we consider situation unlikely in this context and do not pursue it further.

or negative depending on households' starting beliefs and the value of the product relative to its price. The second term is the price anchoring effect, which operates through the gain-loss utility term. It serves to reduce demand by increasing the effective price for both the informed and uninformed as the period-1 price falls. The strength of this effect depends on the shape of the loss function R. Note that the shape of this loss function also affects the effective price in period 2, $\tilde{p}_2$.

Before we proceed with a discussion of the total effect of prices on subsequent demand, we draw the link to the existing literature on experience goods and consider the effect of prices in the absence of gain-loss utility.

Remark 1. *In the absence of gain-loss utility ($R' = 0$), if households are not perfectly informed ($\alpha_1 < 1$) and have unbiased beliefs about the value of the product ($b = 0$), then reducing the price in period 1 will (a) reduce demand in period 2 (π_2) if the period 2-price is above the average value of the product, $p_2 > \bar{v}$, and (b) increase π_2 if $p_2 < \bar{v}$.*

Reducing the price in any period will increase contemporaneous demand and thereby the share of the population that has experience with the product. When some of the population is uninformed, a lower price in the current period increases the share of the population that knows the true value in the next period. The effect of this increase in experience on future demand depends on how the future price compares to the value of the product. When the period-2 price is above the average value, this learning effect tends to decrease demand. Intuitively, when price is above the average value, demand for the product is coming from individuals with positive idiosyncratic shocks (σ_{bit}) to their beliefs about the true value. When more individuals are informed, it is relatively less likely that any given individual will have received shocks large enough to induce them to buy. Expected demand falls. Naturally, the reverse holds when the period-2 price is below the expected value: increasing the informed share of the population increases demand.

We now consider the effect of biased beliefs about the product's value.

Remark 2. *In the absence of gain-loss utility ($R' = 0$), if households are not perfectly informed ($\alpha_1 < 1$) and have biased beliefs about the value of the product ($b \neq 0$), then reducing the price in period 1 ($p_1 = 0$) will (a) reduce demand in period 2 (π_2) if $p_2 > \bar{v} - \frac{\sigma_I}{\sigma_U - \sigma_I} b$ and (b) increase demand in period 2 if $p_2 < \bar{v} - \frac{\sigma_I}{\sigma_U - \sigma_I} b$.*

The additional term in the price cutoff rule, $\frac{\sigma_I}{\sigma_U - \sigma_I} b$, reflects the debiasing effect. Increasing the share of informed individuals not only reduces uncertainty but also reduces the share of individuals with biased beliefs. This makes it more likely that demand in period 2 will decrease if beliefs are optimistic and more likely that demand will increase if they are pessimistic.

We are now in a position to make a prediction about the effect of free distribution on purchase behavior.

Proposition 1. *If individuals are fully informed about the value of the product ($a_1 = 1$) and there is no gain-loss utility ($R' = 0$), then free distribution will have no effect on subsequent demand relative to a distribution at a positive price.*

Intuitively, if individuals are already fully informed and there is no gain-loss utility, then both channels through which prior prices can affect future demand will be shut down. This leads immediately to a hypothesis regarding the presence of gain-loss utility (price anchors) that we can test with the distribution of Panadol, a well-known product for which we can reasonably assume that everyone knows the value.

Assumption 1. *Price reference points are more sensitive to updating after a distribution by an NGO than by a for-profit, that is, $\partial p_t^r / \partial p_{t-1}|_{d=N} > \partial p_t^r / \partial p_{t-1}|_{d=F}$.*

The justification for this assumption was described in the introduction: for-profit companies may be known to offer free samples or steep introductory discounts, but no one expects them to keep giving the product away for free. It leads immediately to our first prediction.

Prediction 1. *In the presence of gain-loss utility, free distributions by an NGO will have a relatively more negative effect on subsequent demand than free distributions by a for-profit.*

It will be useful to define the concept of *scope for learning* by which we mean that (i) at a particular future price the expected demand for a currently informed individual differs from that of an uninformed individual and (ii) not all individuals are informed. We say there is scope for positive learning if $E(\pi_2|Informed, \tilde{p}_2) > E(\pi_2|Uninformed, \tilde{p}_2)$, i.e., at a given price, individuals who are informed about the value of the product would be more likely to purchase than those who are not. Note that this depends on the price. To see this, consider the case where uninformed individuals have unbiased beliefs about the product's value but are simply more uncertain. When the period-2 price is below the average value, it is only those with particularly negative idiosyncratic shocks (σ_{bit}) to their beliefs about the true value who do not buy. When more individuals are informed, it is relatively less likely that any given individual will have received a negative shock large enough to stop her from buying. Naturally, having a pessimistic bias implies that there is more scope for positive learning.

We say there is scope for negative learning if $E(\pi_2|Informed, \tilde{p}_2) < E(\pi_2|Uninformed, \tilde{p}_2)$, i.e., at a given price, individuals who are informed about the value of the product would be less likely to purchase than those who are not. For example, again consider the case where uninformed individuals have unbiased beliefs about the product's value but are simply more uncertain. When the period-2 price is above the average value, demand for the product is coming from individuals with particularly positive idiosyncratic shocks (σ_{bit}) to their beliefs about the true value. When more individuals are informed, it is relatively less likely that any given individual will have received a sufficiently positive shock to induce her to buy and demand falls. Naturally, having an optimistic bias implies that there is more scope for negative learning.

As described in Section 2.1, we make the following assumption about the scope for learning in the three products tested.

Assumption 2. *There is no scope for learning with Panadol, scope for positive learning with Zinkid, and scope for negative learning with Elyzole.*

Taken together, this leads to two additional predictions.

Prediction 2. *The relative effect of the free distribution for Zinkid should be more positive than for Panadol.*

When there is scope for positive learning, an increase in the share of uninformed individuals (a decrease in α_1) will further increase the scope for positive learning. If uninformed individuals are generally pessimistic about a product's true value and a relatively high share of the population is uninformed (as we believe is the case for Zinkid), we expect the effect of a free distribution to be relatively more positive (less negative) than for a free distribution of a well-known product for which there is no scope for learning. Intuitively, as described above, for the well-known product Panadol, if free distribution has any effect on subsequent demand it will be through price anchoring, which will reduce demand. For the product where we would expect to see positive learning, Zinkid, this effect would be offset by increasing the share of informed individuals and hence increasing expected demand.

Prediction 3. *The relative effect of free distribution for Elyzole should be more negative than for Panadol.*

When there is scope for negative learning (e.g., uninformed individuals have optimistic beliefs about the product's value), an increase in the share of uninformed individuals (a decrease in α_1) will further increase the scope for negative learning and amplify the effects of free distribution. For example, if uninformed individuals are generally optimistic about a product's true value and a relatively high share of the population is uninformed, we expect the effect of a free distribution to be relatively more negative than for a free distribution of a well-known product for which there is no scope for learning. Intuitively, because there is scope for negative learning for Elyzole, free distribution will tend to decrease subsequent demand through the learning channel in addition to any effect of price anchors.

These predictions highlight the potential importance of price anchors in determining the optimal pricing for experience goods. Lowering the current price will increase the share of individuals who purchase in the current period and hence who are informed about product quality in the future. The effect of this learning depends on the share of uninformed, the mean bias in the population and the value of the product relative to the price. However, the price anchoring effect can offset the potential increase in demand from learning, thus depressing demand in aggregate.

4 Results

In our setting, free health goods can affect demand through two different mechanisms: price anchoring and learning. We generated exogenous variation along three dimensions: whether a product was offered for free or for sale in Wave 1, whether it was offered by an NGO or a for-profit company in Wave 1, and the product a household was offered. The product price and the type of distributing organization were randomly assigned at the village level, while the product type was assigned at the household level. To estimate our treatment effects, we run the following basic specification for each product k

$$y_{ijkt} = \beta_{k0} + \beta_{k1} NGO_{ij} + \beta_{k2} Free_{ij} + \beta_{k3} Free_{ij} \times NGO_{ij} + \gamma_k X_{ij} + \varepsilon_{ijkt}, \qquad (4)$$

where y is a measure of demand (either a binary indicator of take-up or the total quantity purchased/received), i represents households, j represents villages, and t represents time (Wave 1 or Wave 2). NGO is a dummy variable that takes the value 1 if a household was approached by a representative of an NGO in Wave 1 and 0 if approached by a for-profit. The dummy variable $Free$ takes the value 1 if a household was offered the product for free in Wave 1 and 0 otherwise. Coefficients of interest are the betas. β_1 captures the effect of an NGO being the distributing organization in Wave 1, β_2 the effect of being offered a product for free in Wave 1, and β_3 the effect of the interaction, i.e., being offered a free product by an NGO in Wave 1. X_{ij} is the vector cross product of the two stratification variables: a price index and a remoteness index. ε_{ijt} represents the idiosyncratic error, which we cluster at the village, the level of randomization.[28] We estimate equation (4) for the pooled sample and for each product individually.

Inline with the core predictions of the theory and to facilitate interpretation, we also estimate for each product k a specification that excludes the NGO terms

$$y_{ijkt} = \beta_{k0} + \beta_{k4}Free_{ij} + \gamma_k X_{ij} + \varepsilon_{ijkt}. \tag{5}$$

4.1 Take-up in Wave 1

Table 3 shows the results, by product, from estimating equation (4) for Wave 1. The odd numbered columns show the effects of treatment assignment on take up defined as a binary variable equal to 1 if a household purchased or accepted any quantity of the offered product and 0 otherwise. The even numbered columns report the quantity effects as measured in units of the product.[29]

[28] Stratification was primarily done to ensure balance. Although power is limited for subsample analyses, we do examine whether results are heterogeneous regarding remoteness and price levels. The results do not exhibit any significant heterogeneity along these dimensions.

[29] The unit for Panadol is a strip of ten pills, the unit for Elyzole is one dose for an adult, which corresponds to three boxes of two tablets each, and the unit for Zinkid/ORS is a pill strip of ten Zinkid tablets combined

Unsurprisingly, take up was much higher among those who were offered health products for free compared to those offered them for sale. As the odd-numbered columns show, among households in the for-profit group, being offered the product for free increased binary take up by 46.3 percentage points for Elyzole, 23.7 percentage points for Panadol, and 69.9 percentage points for Zinkid. All coefficients are statistically significant with p-values below 0.01.[30]

The effect of free distribution on the quantity received follows a similar pattern for Elyzole and Zinkid: those in the Free treatment were not only more likely to receive any of the assigned product but also received more of the product on average. However, the Sale treatment increased the average quantity of Panadol obtained by 0.732 units (or 73.2 percent) relative to the Free treatment. As described above, households in the Sale treatment could purchase up to five units of the assigned product while distribution in the Free treatment was limited to one unit per household. In the case of Panadol, this leads to a reversal in the sign of the treatment effect between the binary and quantity regressions. While not all of the households in the Sale treatment purchased the product, those who did so purchased more than one unit on average.

Table 3 also shows that in the case of the unknown product (Zinkid), households were substantially more likely to purchase the product when it was offered for sale by a NGO rather than a for-profit entity. This difference is both statistically and economically significant: a 15.9 percentage point increase in take up and a 50.7 percent increase in total quantity purchased. Recall that the marketing scripts differed only in their description of the seller's identity and motives. All information presented about the product itself was identical across the four treatment arms. Differences in the take-up rate could result ei-

with one sachet of oral rehydration salts.

[30]The results in Table 3 for "any purchase" (the odd columns) are robust to using a Probit specification for the binary outcome variable. Those for the quantity purchased (the even columns) are robust to the Tobit specification, which accounts for left censoring of the dependent variable at zero and right censoring at 1 or 5 units, depending on the treatment group.

ther from differences in how households interpreted marketing information about product quality (e.g., the NGO was considered more accurate or trustworthy) or from how they perceived the offer prices (e.g., when offered by the NGO a price was considered a "better deal"). For the more well-known products, no such difference is evident.

Qualitative results from the post-marketing survey suggest a potential mechanism. Those offered Zinkid for sale by the NGO were more likely than those in the for-profit treatment to cite the product's health benefits as a reason for purchase (p-value: 0.059); however, they were no more likely to state "I purchased this because I trust you." We speculate that the results may still reflect a greater trust in the NGO when considering new products, but individuals are not explicitly aware of the NGO's role in forming their impressions. The magnitude of this effect is large: take-up increases from 30 percent to 46 percent. This is consistent with other emerging work that points to the potential role of non-profit organizations as trust builders and may have important policy implications for organizations seeking to encourage the adoption of new technologies (Cole et al., 2013; Karlan, 2014). While our study design does not allow us to speak further to the mechanisms behind this effect, we believe future research into the role played by NGOs in stimulating demand for new products would be valuable.

4.2 Demand in Wave 2

Next we investigate the core question of the study: what is the impact on future demand of distributing the products for free. As described in Section 3, in our setting, the impact of free distribution consists of two basic effects: a price anchoring effect that may depress demand and an information effect whose direction depends on whether the potential for learning is primarily positive or negative.

First, we examine the results pooled across all three products. Table 4 column 1 presents the effect on the extensive (Panel A) and intensive (Panel B) margins. In both cases, we find that the provision of free products depresses demand approximately ten weeks later, with take-up after a free distribution 10 percentage points lower than after a distribution at market prices. However, note that this result pools three products that we deliberately chose, not some naturally occurring set of products. The pooled test demonstrates evidence of price anchors, but cannot shed insight into the trade-off between learning and reference points. For that, we must examine the products individually.

For each of the three products offered in Wave 1, subsequent demand is lower in Wave 2 if the product was initially offered for free. For Panadol and Elyzole, the results are substantial and statistically significant. As shown in Panel A, columns 2 and 3, those previously receiving the product for free are 9.1 percentage points (s.e.=2.8) and 12.0 percentage points (s.e.=4.1) less likely to purchase any of the product in Wave 2. In the case of Zinkid, for which there is scope for positive learning, the effect is muted. Demand for Zinkid in the Free treatment group is 5.3 percentage points (s.e.=3.7) lower than in the Sale treatment, but the difference is not statistically significant (column 4). Panel B displays results for the quantity of units purchased. Again, the effect of prior free distribution is negative and substantial for both Panadol and Elyzole, a reduction in the quantity purchased of 24.5% and 23.0%, respectively; however, the effect for Elyzole is not statistically significant at conventional levels (p-value: 0.116). The effect of prior free distribution of Zinkid, the product with scope for positive learning, is negligible.

We cannot compare the purchase rate across time in order to determine whether the free distribution reduced demand in absolute terms or merely relative to a sales distribution. Unfortunately, such an analysis would not be valid as the two distribution waves occurred at different times in the year and demand is subject to seasonal variation. Furthermore, when considering pricing policy, the counterfactual of no distribution at any price is not relevant. Rather, the relative difference between high and low prices—or between positive and zero—represents the critical parameter of interest.

Finally, we do not find evidence that the anchoring effect of free distributions spills over to other health products. Column 4 reports the effect of Wave 1 treatment status on the Wave 2 purchase decisions for a new product, Aquasafe. Note that because there is no reason to suspect cross-product learning, this is a test of whether free distribution of one health product moves the reference point for another. Naturally, this is not dispositive. We are testing potential cross-product spillovers from one of three particular products to another product offered by a different organization. We cannot reject the null of no effect. While the 95%-confidence interval rules out a cross-product effect as large as the own effect of free distribution for Panadol or Elyzole, it remains quite large with a 95%-confidence interval from -8.7 to +6.7 percentage points. We also do not see statistically significant differences between prior distribution by an NGO and prior distribution by a for-profit, though our estimates are imprecise.

4.3 Discussion and alternative explanations

The empirical results show that demand following a free distribution can be lower than following distribution at a market price. Here we first consider the qualitative evidence in support of price anchors and then consider alternative mechanisms.

Qualitative evidence from the post-marketing questionnaire supports the role of price anchors in reducing relative demand following a free distribution. After the Wave 2 distribution, the marketers asked all respondents why they made their purchase decisions. The question was asked in an open-ended way without prompting, and surveyors coded the responses into predetermined categories based on piloting of survey questions. As is shown in Figure 1, among those who decided not to purchase the offered good in Wave 2, 10.4 percent of respondents in the Free treatment stated that they did not purchase the product because either they or others whom they knew had previously been given it for free. In contrast, only 2.2 percent of those in the Sale treatment responded similarly (p-value: 0.000). A further 4.1 percent of the Free treatment group stated that the product was too expensive versus 1.7 percent in the Sale group (p-value: 0.027). While these responses are subject to all the usual qualifications regarding self-reported explanations for behavior, the Wave 2 distributors were affiliated with a different entity than either of those seen in Wave 1, ameliorating concerns over experimenter demand effects. Furthermore, there is little reason to expect differential survey effects across treatment groups. Taken at face value, these responses would explain the entire difference in Wave 2 purchase behavior between the Free and Sale treatments.

Next, we assess the plausibility of eight alternative mechanisms that could explain differential effects between free and priced distributions. These include (i) stock on hand, (ii) expectations of a pricing regime change, (iii) income effects, (iv) liquidity constraints, (v) externalities, (vi) habit formation, (vii) prices as a signal of quality, and (viii) cognitive costs. Below we consider each in turn.

First, we consider what is perhaps the most obvious alternative mechanism through which free distribution could reduce future demand: stock. Those people who received a product for free in Wave 1 may not purchase in Wave 2 simply because they still have a stock of the relevant product at home. Our usage measures and qualitative surveys were designed to assess the importance of this mechanism. Both speak against stock driving the results.

Table 5 reports measures of experimentally-provided stock on hand before Wave 2. For Panadol and Elyzole, the two products for which we saw a significant negative effect from prior free distribution, stock in the Free treatment group is no higher than in the Sale group. In fact, due to differences across treatments in the maximum quantity available per household (see Section 4.1 for details), average experimentally-provided stock-on-hand in the Sale treatment of the Panadol group was actually larger than in the Free treatment. To the extent that stock-on-hand did affect demand, it would have made households who were offered Panadol for free in Wave 1 slightly more—not less—likely to purchase in Wave 2, suggesting that our estimate is a lower bound on the magnitude of the effect.

In the case of Zinkid, those in the Free treatment did have more tablets remaining. To the extent that stock affects demand, this should lower relative demand for those in the Free treatment. In contrast to the other two products, this suggests that our estimates would be an upper bound on the magnitude of the effect. However, Zinkid, the product for which we expected some scope for positive learning, is the product for which we do not find a statistically significant negative effect of free distribution on Wave 2 demand.

The preceding results examine only the remaining experimental stock and do not consider the household's overall stock, which could be obtained from other sources. To address this, we asked respondents in a post-marketing survey why they did not purchase products in Wave 2. As Figure 1 shows, we do not find a higher share of respondents in the Free group giving "I already have enough of it" as reason for not purchasing. If anything, the share is higher in the Sale group, but the differences are not statistically significant. Taken together, we consider this convincing evidence that stock is not driving the reduction in demand following a free distribution.[31]

A second potential alternative mechanism is a regime change story. Suppose that prior to our intervention people believed that Panadol was always sold and never given away for

[31] We note that one potential drawback is that we do not have data on the purchases of the products outside of our marketing visits; however, we do not see this as a risk to the study. The products we offered were available for sale in local drug shops in 11%-36% of the study villages (see Table 1). While it is possible that some individuals did not purchase in Wave 2 because they had purchased from a local shop, no respondent indicated this a reason for not purchasing in the post-marketing surveys. Outside purchases were not an enumerated option in the post-marketing survey because they were not mentioned during piloting. The question regarding the reasons for not purchasing was unprompted and, while an "other" option was available, outside purchases were not mentioned. We also note that there is no distinguishable difference in the effect of prior free distribution on subsequent demand between those villages where the product was available for outside purchase and those where it was not.

free.[32] Suppose further that there was significant uncertainty about the pricing regime for Zinkid. Since it is a largely unknown product, people could believe it may or may not be given away for free. If the individuals who received Panadol for free in Wave 1 believed that this indicated a regime change—that Panadol would now be distributed occasionally for free—this may have had a larger effect on their price reference point than for Zinkid. While we consider this a plausible mechanism following free distribution by an NGO, we do not find it credible in the case of for-profit distribution. There is no reason to think that for-profits would shift to a give-it-away-for-free-always regime. Yet, we do not find a difference in treatment effects between the NGO and the for-profit group for Zinkid (see column 4 in Table 4). Thus, we rule out regime change.

A third potential mechanism is income effects. People who received the health products may have lost fewer work days due to illness during the ten weeks between the two waves and thus may have had more disposable funds to purchase products in the second wave of marketing. If an income effect existed, this would have increased relative demand in the Free group and would therefore imply that we are underestimating the price anchoring effect. It is worth noting that in contrast to insecticide-treated bed nets, where income effects could exist, we expect any income effects of the products in this study to be relatively modest.

Fourth, liquidity may have affected demand. Since households who received the product for free effectively received a transfer, they may have had more money available when marketers appeared in Wave 2. However, any effect along this dimension would tend to increase demand in the Free treatment. We would also expect any effects to be quite small. The magnitude of the transfer was low—about $0.80 per household. Moreover, villages were revisited approximately ten weeks later and this future visit was not announced at the

[32] Indeed, according to our village leader survey, only in 1 out of 120 villages had Panadol ever been distributed door-to-door for free.

time of the first. It seems implausible that people kept the funds they would have otherwise spent on drugs in Wave 1 for a full ten weeks. Finally, to mitigate liquidity constraints, flyers were distributed a few days prior to each marketing visit to allow respondents to get money ready.

A fifth possible mechanism affecting demand is positive externalities. The argument here would be that higher take-up in Wave 1 reduced disease prevalence and hence the utility from purchasing the product in Wave 2. However, an externality argument cannot explain the negative effect on demand in Wave 2 from free distribution for Panadol, since it is implausible that pain killers have externalities. In contrast, the deworming medicine Elyzole does have positive externalities. Dewormed children are less likely to transmit worms to their siblings and peers (Miguel and Kremer, 2004; Ozier, 2011), which could explain a negative effect of free distribution on later demand. However, to the extent that such effects were present in our study, we expect that they were quite small. On average, we distributed Elyzole to only about five percent of households per village in Wave 1. As such, any reduction in disease loads and hence the utility of purchase in Wave 2 would have been quite small.

Sixth, habit formation may have influenced demand. Suppose that upon receiving the health products, households become habituated to using them. Habit formation would make it more likely that households who received the product in Wave 1 then purchase the product in Wave 2, regardless of the direction of learning effects. Since a higher share of households received the products in the villages assigned to the Free treatment, habit formation should have a positive effect on demand there. In contrast, our results move in the opposite direction.

Seventh, higher prices may signal higher quality (Milgrom and Roberts, 1986; Heffetz and Shayo, 2009; Ashraf et al., 2013). All else equal, being offered a product for a higher price should then increase later demand just as we would expect from the price anchoring model. However, the signaling mechanism should have a larger effect for products with more uncertainty about the benefits and would have the exact opposite effect of our model of experience learning, i.e., positive prices should increase relative demand for the least well-known products. While our point estimates across products are in line with the anchoring mechanism rather than the quality signal alternative, we again note that the differences in these estimates are not statistically significant. We cannot rule out the possibility that prices as a signal of quality may explain some of the differences in demand following free and sale distributions. Since these mechanisms have distinct policy implications, we think further research to distinguish their effects would be useful.

Finally, cognitive costs of determining a product's value may influence our results. Suppose that any time individuals are faced with a positive price on a less well established product, they have some probability of being willing to incur the cognitive cost of determining their own valuation for the product. Without first having determined their valuation, they do not buy, since they are uncertain whether the price is above or below their personal valuation of the good. Then, being repeatedly exposed to a purchase decision should increase purchase rates, since in every subsequent interaction fewer and fewer people need to incur the cognitive cost. However, we find the negative effect of free distribution on Wave 2 purchase decisions also for Panadol, a product for which beliefs should be well established, thus no cognitive costs should be necessary to determine its value. This suggests that cognitive costs are not the only mechanism driving our results.

5 Conclusion

We examine the pricing policy trade-off between learning and price anchors. To do this, we design and implement a field experiment in northern Uganda and find evidence of exactly such a trade-off. Consistent with models of reference-dependent preferences (Kőszegi and

Rabin, 2006; Mazar et al., 2013; Heidhues and Kőszegi, 2014), free distribution lowers subsequent demand.

To study the trade-off between learning and price anchors, we then examine individually three products specifically chosen to span a range of potential learning effects. For the two products without potential for positive learning (Panadol & Elyzole, for pain relief and deworming, respectively), we find that subsequent demand is lower after a free distribution than after a sales distribution. For Zinkid, which we argue has potential for positive learning, we do not find such an effect. Positive learning appears to offset the price anchoring effect. However, although each of the above stated results is statistically significant, the differences across the products are not. We note that the predictions of our model match the rank ordering of the demand effects when computed in percentage point terms, the standard unit of measurement in this literature, which focuses on coverage rates for their policy relevance. When calculated in percent terms, only two of the three pairwise comparisons match the theoretical predictions, with the negative effect from free distribution of Zinkid being slightly larger than for Panadol despite the potential for positive learning about Zinkid. We rule out plausible alternative mechanisms, most importantly stock, and report additional, qualitative evidence supporting reference dependence as the mechanism behind lower demand.

Our results help reconcile empirical findings from marketing and psychology demonstrating a large role for price anchors with those from recent field experiments in the context of health goods in low-income countries, which find no evidence that prices have meaningful non-budget-constraint effects. While lower prices today can dampen future demand by setting low price reference points, opportunities to positively update one's beliefs about a product's value may blunt this effect. We also examine whether price anchors for one product spill over to the demand for another. While we do not find evidence of such spillovers, we also note that this test is under-powered compared to the other tests put forward. Given the potential importance of categorical price judgments, such cross-product spillovers remain an important area for future research.

Surprisingly and in contrast to our expectations, we find that the identity of the distributor does not affect the degree of price anchoring. The relative drop in demand following free distributions is the same whether the product was offered by a for-profit entity or an NGO.

We find that the identity of the distributor does matter for the sale of the lesser-known product, Zinkid, suggesting an important role for NGOs in providing quality signals for developing markets. Individuals offered this product for sale by the NGO were 16 percentage points (over 50 percent) more likely to purchase than those who were offered it by the for-profit. The effect does not persist to the subsequent distribution by a third-party, for-profit; however, the immediate observed effect is economically large and further research along this dimension could provide welcome insight into how to most effectively introduce new products, particularly in low-income countries (Cole et al., 2013; Karlan, 2014).

We contribute to three distinct strands of research. First, we provide additional evidence for the importance of price anchors in an important, non-laboratory domain of economic behavior. Second, we build on Dupas (2014) to contribute to the literature on experience goods pricing (Nelson, 1970; Villas-Boas, 2004; Shapiro, 1983; Bergemann and Välimäki, 2006) by highlighting the essential tension between learning and the potential for prices to directly affect potential consumers' willingness to pay. Our study design highlights the insight that the impact of free distribution on later demand depends critically on whether users have a positive or negative experience with the product. This mechanism may be particularly important in the case of pharmaceutical demand (Crawford and Shum, 2005) but is also applicable to agricultural products and other goods where subsidies or discounts are common policy instruments.

Third, we directly inform the often controversial debate on subsidized distribution of health products, particularly in low-income countries. The motivations for free or subsidized distribution are numerous: to account for positive externalities (Miguel and Kremer, 2004), to provide people an opportunity to learn about the value of the good (Dupas, 2014), to account for behavioral biases that lead to suboptimal purchase rates (Baicker et al., 2012), and to redress social injustices (Ponsar et al., 2011). The reasons against free distribution typically focus on concerns about dampening long-term demand or generating short-term sunk costs effects whereby a product received for free is not valued and hence not used (Cohen and Dupas, 2010).

We note several considerations regarding generalizability. The experimental setting of northern Uganda has a large NGO presence and a history of free distribution. In principle, this could either dampen the effect—because our marketing campaign is a small part of individuals' experience with free distributions—or amplify it if individuals have become accustomed to the activities of NGOs and thus more attuned to any deviations from norms regarding which specific products get subsidized. We also only examine only curative products, not preventive ones. For many reasons (mean reversion, attribution bias, frequency and proximate nature of information, and salience, for example) individuals may update beliefs more rapidly after using curative products relative to preventive products (particularly for infrequent illnesses).

Finally, we note several methodological lessons from our exercise. First, this was a fairly large study but still was hampered by statistical power concerns when testing separately across products. This is often the case when examining heterogeneous treatment effects. For this particular question, having micro-level data on both consumers' willingness-to-pay at baseline (e.g., as done in Berry et al., 2015) or on consumers' knowledge and beliefs would have improved power. The methodological tradeoff is the loss of some of the "naturalness" of the exercise as implemented in this study. Second, while it would entail another tradeoff against naturalness, entrance into the sample frame should be done identically for all treatment groups. Whereas in our setup we did not have differential attrition from Wave 1 to Wave 2, the flyers distributed in anticipation of the study, intended to follow normal marketing procedures, did generate a higher entrance-into-the-sample rate for the free distribution versus the sale. Third, conducting this type of experiment in settings with more diversity of market conditions (e.g., with respect to the presence and pricing of drugs) would provide a valuable opportunity to examine how local market conditions influence the results. Fourth, building this exercise on top of other long-term data collection would produce important economies of scale in operations and also provide access to richer baseline and long-term data. This would allow researchers to examine everything from more nuanced heterogeneous treatment effects to long-term usage, welfare and market responses.

Although the experiment was setup in a particular setting, integrating NGO and for-profit activity in rural Uganda, the theory purposefully abstracts from this and other potentially important factors in order to highlight the tension between learning and price anchoring effects. The theoretical model could be extended and subsequent experiments designed around testing such extensions. For instance, variation in income effects, externalities, duration, information, cognitive costs and environmental factors such as prior pricing history are all important considerations for pricing experience goods. This applies for firms aiming to maximize the net present value of profits and policymakers aiming to increase social welfare. These considerations as well as a number of other parameters from which we abstract should influence pricing policy for a specific product type, in specific market conditions, to specific household types. The question of whether "to charge or not to charge?" should not be answered generically.

References

Adaval, Rashmi and Kent B Monroe, “Automatic Construction and Use of Contextual Information for Product and Price Evaluations,” *Journal of Consumer Research*, 2002, *28* (4), 572–588.

— **and Robert S Wyer Jr**, “Conscious and Nonconscious Comparisons With Price Anchors: Effects on Willingness to Pay for Related and Unrelated Products,” *Journal of Marketing Research*, 2011, *48* (2), 355–365.

Ahmed, Siraj F., Farheen A, Muzaffar A, and Mattoo G. M, “Prevalence of Diarrhoeal Disease, Its Seasonal and Age Variation in Under-Fives in Kashmir, India,” *International Journal of Health Sciences*, 2008, *2* (2), 126–133.

Alba, Joseph W., Carl F. Mela, Terence A. Shimp, and Joel E. Urbany, “The Effect of Discount Frequency and Depth on Consumer Price Judgments,” *Journal of Consumer Research*, 1999, *26* (2), 99–114.

Anderson, Eric T. and Duncan I. Simester, “Long-Run Effects of Promotion Depth on New Versus Established Customers: Three Field Studies,” *Marketing Science*, 2004, *23* (1), 4–20.

Ariely, Dan, George Loewenstein, and Drazen Prelec, "“Coherent Arbitrariness": Stable Demand Curves Without Stable Preferences,” *The Quarterly Journal of Economics*, 2003, *118* (1), 73–106.

Ashraf, Nava, B. Kelsey Jack, and Emir Kamenica, “Information and Subsidies: Complements or Substitutes?,” *Journal of Economic Behavior & Organization*, 2013, *88*, 133–139.

— **, James Berry, and Jesse M. Shapiro**, “Can Higher Prices Stimulate Product Use? Evidence from a Field Experiment in Zambia,” *American Economic Review*, 2010, *100* (5), 2383–2413.

Baicker, Katherine, Sendhil Mullainathan, and Joshua Schwartzstein, “Behavioral Hazard in Health Insurance,” Working Paper 18468, National Bureau of Economic Research, October 2012.

Bergemann, Dirk and Juuso Välimäki, “Learning and Strategic Pricing,” *Econometrica*, 1996, *64* (5), 1125–1149.

— **and** — , “Dynamic Pricing of New Experience Goods,” *Journal of Political Economy*, 2006, *114* (4), 713–743.

Berry, Jim, Greg Fischer, and Raymond Guiteras, “Eliciting and Utilizing Willingness-to-Pay: Evidence from Field Trials in Northern Ghana,” 2015. BREAD Working Paper.

Chapman, Gretchen B and Eric J. Johnson, "Anchoring, activation, and the construction of values," *Organizational Behavior and Human Decision Processes*, 1999, *79* (2), 115–153.

Cohen, Jessica and Pascaline Dupas, "Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Prevention Experiment," *The Quarterly Journal of Economics*, 2010, *125* (1), 1–45.

Cole, Shawn, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery, "Barriers to Household Risk Management: Evidence from India," *American Economic Journal: Applied Economics*, 2013, *5* (1), 104–135.

Crawford, Gregory S. and Matthew Shum, "Uncertainty and Learning in Pharmaceutical Demand," *Econometrica*, 2005, *73* (4), 1137–1173.

da Cunha, Ferreira RM and RA Cash, "History of the Development of Oral Rehydration Therapy," *Clinical Therapeutics*, 1989, *12*, 2–11.

Das, Jishnu, Jeffrey Hammer, and Kenneth Leonard, "The Quality of Medical Advice in Low-Income Countries," *Journal of Economic Perspectives*, 2008, *22* (2), 93–114.

Dekimpe, Marnik G., Dominique M. Hanssens, and Jorge M. Silva-Risso, "Long-run Effects of Price Promotions in Scanner Markets," *Journal of Econometrics*, 1998, *89* (1), 269–291.

Doob, Anthony N, J Merrill Carlsmith, Jonathan L Freedman, Thomas K Landauer, and Soleng Tom Jr, "Effect of Initial Selling Price on Subsequent Sales," *Journal of Personality and Social Psychology*, 1969, *11* (4), 345.

Dupas, Pascaline, "Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence from a Field Experiment," *Econometrica*, 2014, *82* (1), 197–228.

Epley, Nicholas and Thomas Gilovich, "Putting Adjustment Back in the Anchoring and Adjustment Heuristic: Differential Processing of Self-Generated and Experimenter-Provided Anchors," *Psychological Science*, 2001, *12* (5), 391–396.

Fitzpatrick, Anne, "Do Informed Consumers Reduce the Price and Prevalence of Counterfeit Drugs? Evidence from the Antimalarial Market," 2014. University of Michigan Department of Economics Working Paper.

Freedman, Stephen B, Dennis Cho, Kathy Boutis, Derek Stephens, and Suzanne Schuh, "Assessing the Palatability of Oral Rehydration Solutions in School-aged Children: A Randomized Crossover Trial," *Archives of Pediatrics & Adolescent Medicine*, 2010, *164* (8), 696–702.

Fudenberg, Drew, David K Levine, and Zacharias Maniadis, "On the Robustness of Anchoring Effects in WTP and WTA Experiments," *American Economic Journal: Microeconomics*, 2012, *4* (2), 131–145.

Hahn, Seokyung, S Kim, and Paul Garner, "Reduced Osmolarity Oral Rehydration Solution for Treating Dehydration Caused by Acute Diarrhoea in Children," *Cochrane Database of Systematic Reviews*, 2002, *1.*

Heffetz, Ori and Moses Shayo, "How Large Are Non-Budget-Constraint Effects of Prices on Demand?," *American Economic Journal: Applied Economics*, 2009, *1* (4), 170–199.

Heidhues, Paul and Botond Kőszegi, "Regular Prices and Sales," *Theoretical Economics*, 2014, *9* (1), 217–251.

J-PAL Policy Bulletin, *The Price is Wrong* Abdul Latif Jameel Poverty Action Lab 2011.

Jacowitz, Karen E and Daniel Kahneman, "Measures of Anchoring in Estimation Tasks," *Personality and Social Psychology Bulletin*, 1995, *21*, 1161–1166.

Kalwani, Manohar U. and Chi Kin Yim, "Consumer Price and Promotion Expectations: An Experimental Study," *Journal of Marketing Research*, 1992, *29* (1), 90–100.

Kalyanaram, Gurumurthy and John Little, "An Empirical Analysis of Latitude of Price Acceptance in Consumer Package Goods," *Journal of Consumer Research*, 1994, pp. 408–418.

Karlan, Dean, "The Next Stage of Financial Inclusion," *Stanford Social Investment Review*, Fall 2014, pp. 43–49.

Kopalle, Praveen K and Joan Lindsey-Mullikin, "The Impact of External Reference Price on Consumer Price Expectations," *Journal of Retailing*, 2003, *79* (4), 225–236.

Kőszegi, Botond and Matthew Rabin, "A Model of Reference-Dependent Preferences," *The Quarterly Journal of Economics*, 2006, *121* (4), 1133–1165.

Larson, Charles P., Unnati Rani Saha, and Hazera Nazrul, "Impact Monitoring of the National Scale Up of Zinc Treatment for Childhood Diarrhea in Bangladesh: Repeat Ecologic Surveys," *PLoS medicine*, 2009, *6* (11), e1000175.

Maniadis, Zacharias, Fabio Tufano, and John A. List, "One Swallow Doesn't Make a Summer: New Evidence on Anchoring Effects," *The American Economic Review*, 2014, *104* (1), 277–290.

Mayhew, Glenn E and Russell S Winer, "An Empirical Analysis of Internal and External Reference Prices using Scanner Data," *Journal of Consumer Research*, 1992.

Mazar, Nina, Botond Kőszegi, and Dan Ariely, "True Context-Dependent Preferences? The Causes of Market-Dependent Valuations," *Journal of Behavioral Decision Making*, 2013.

Miguel, Edward and Michael Kremer, "Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities," *Econometrica*, 2004, *72* (1), 159–217.

Milgrom, Paul and John Roberts, "Price and Advertising Signals of Product Quality," *Journal of Political Economy*, 1986, *94* (4), 796–821.

Ministry of Health, Republic of Uganda, "National Guidelines for Management of Common Conditions," The Ministry of Health Uganda 2012.

Nelson, Phillip, "Information and Consumer Behavior," *Journal of Politcal Economy*, 1970, *78* (2), 311–329.

Nunes, Joseph C. and Peter Boatwright, "Incidental Prices and Their Effect on Willingness to Pay," *Journal of Marketing Research*, 2004, *41* (4), 457–466.

Ozier, Owen, "Exploiting Externalities to Estimate the Long-term Benefits of Early Childhood Deworming," 2011. Working Paper.

Ponsar, Frédérique, Michel Van Herp, Rony Zachariah, Mit Phillips Gerard Séco, and Guillaume Jouquet, "Abolishing User Fees for Children and Pregnant Women Trebled Uptake of Malaria-related Interventions in Kangaba, Mali," *Health Policy and Planning*, 2011, *26* (suppl 2), ii72–ii83.

Raghubir, Priya and Kim Corfman, "When Do Price Promotions Affect Pretrial Brand Evaluations?," *Journal of Marketing Research*, 1999, *36* (2), 211–222.

Rao, Akshay R. and Kent B. Monroe, "The Effect of Price, Brand Name, and Store Name on Buyers' Perceptions of Product Quality: An Integrative Review," *Journal of Marketing Research*, 1989, *26* (3), 351–357.

Sanders, Emily, Kathryn Banke, Julie Williams, and Vicki MacDonald, "Introducing Zinc Through the Private Sector in Benin: Evaluation of Caregiver Knowledge Attitudes and Practices 2009 and 2011," Technical Report, Abt Associates Inc., Bethesda, MD 2013.

Shapiro, Carl, "Optimal Pricing of Experience Goods," *The Bell Journal of Economics*, 1983, *14* (2), 497–507.

Sherif, Muzafer, Daniel Taub, and Carl I. Hovland, "Assimilation and Contrast Effects of Anchoring Stimuli on Judgments," *Journal of Experimental Psychology*, 1958, *55* (2), 150.

Simonsohn, Uri and George Loewenstein, "Mistake #37: The Effect of Previously Encountered Prices on Current Housing Demand," *The Economic Journal*, 2006, *116* (508), 175–199.

Tarozzi, Alessandro, Aprajit Mahajan, Brian Blackburn, Dan Kopf, Lakshmi Krishnan, and Joanne Yoong, "Micro-loans, Insecticide-Treated Bednets, and Malaria: Evidence from a Randomized Controlled Trial in Orissa, India," *American Economic Review*, 2014, *104* (7), 1909–41.

Tirole, Jean, *The Theory of Industrial Organization*, Cambridge, MA: MIT Press, 1988.

Tversky, Amos and Daniel Kahneman, "Judgment under Uncertainty: Heuristics and Biases," *Science*, 1974, *185* (4157), 1124–1131.

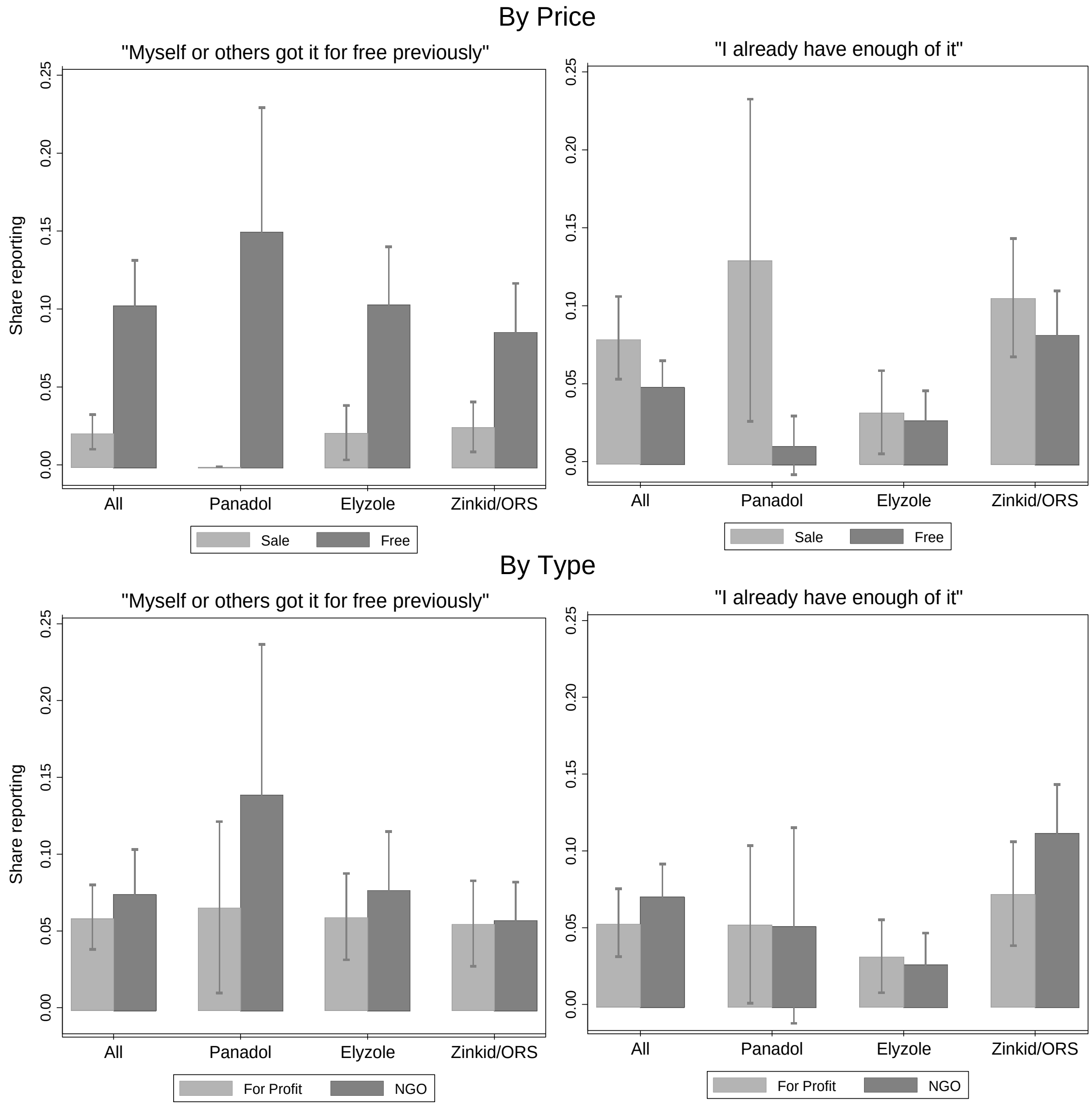
United Nations Secretary General, *The Millennium Development Goals Report* United Nations Secretary General 2009.

Villas-Boas, J. Miguel, "Consumer Learning, Brand Loyalty, and Competition," *Marketing Science*, 2004, *23* (1), 134–145.

Winer, Russell S., "A Reference Price Model of Brand Choice for Frequently Purchased Products," *Journal of Consumer Research*, 1986, *13* (2), 250–256.

World Health Organization, *The Treatment of Diarrhoea: A Manual for Physicians and Other Senior Health Workers* World Health Organization, Geneva: WHO Press, 2005.

Figure 1: Reasons for Not Purchasing, Wave 2



Note. Share of respondents reporting a specific reason for not purchasing the offered product in Wave 2 conditional on not purchasing. Multiple responses were allowed. Whisker bars represent 90%-confidence intervals

Table 1: Baseline Summary Statistics
Means & Standard Deviations

	Wave 1 Treatment Assignment				p-value of		
	Free	Sale	NGO	For-Profit	(1) vs (2)	(3) vs (4)	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Wave 1 Respondents							
Individual Level							
Female	0.529	0.538	0.516	0.550	0.572	0.031	3879
	(0.499)	(0.499)	(0.500)	(0.498)			
Respondent age	42.984	42.781	43.214	42.545	0.827	0.468	1016 [a]
	(14.579)	(14.762)	(14.511)	(14.813)			
Number of children under 16	4.475	4.339	4.378	4.457	0.363	0.596	1016 [a]
	(2.417)	(2.287)	(2.368)	(2.356)			
Wealth proxy (cows owned)	1.058	0.874	0.893	1.070	0.228	0.242	1016 [a]
	(2.601)	(2.137)	(2.365)	(2.459)			
Visited for usage check	0.080	0.090	0.085	0.085	0.249	0.980	3879
	(0.271)	(0.287)	(0.279)	(0.279)			
Found in Wave 2	0.747	0.742	0.765	0.723	0.737	0.003	3879
	(0.435)	(0.438)	(0.424)	(0.447)			
Village Level							
Number of drug outlets	1.167	1.367	1.167	1.367	0.483	0.483	120
	(1.452)	(1.657)	(1.520)	(1.594)			
Panadol available[b]	0.383	0.333	0.333	0.383	0.572	0.572	120
	(0.490)	(0.475)	(0.475)	(0.490)			
Elyzole available[b]	0.233	0.250	0.217	0.267	0.833	0.526	120
	(0.427)	(0.437)	(0.415)	(0.446)			
Zinkid available[b]	0.117	0.100	0.100	0.117	0.771	0.771	120
	(0.324)	(0.303)	(0.303)	(0.324)			
Reports free distribution of any	0.500	0.483	0.433	0.550	0.857	0.204	120
drug in last 3 mo.[c]	(0.504)	(0.504)	(0.500)	(0.502)			
Reports free distribution of any	0.467	0.450	0.383	0.533	0.856	0.101	120
deworming drug in last 3 mo.[c]	(0.503)	(0.502)	(0.490)	(0.503)			
Reports free distribution of	0.050	0.050	0.033	0.067	1.000	0.406	120
Elyzole in last 3 mo.[c]	(0.220)	(0.220)	(0.181)	(0.252)			
Panel B: Wave 2 Respondents							
Female	0.509	0.509	0.489	0.530	0.988	0.025	2887
	(0.500)	(0.500)	(0.500)	(0.499)			
Respondent age	43.507	42.979	43.685	42.783	0.620	0.395	779 [a]
	(14.783)	(14.601)	(14.184)	(15.307)			
Number of children under 16	4.523	4.383	4.456	4.470	0.423	0.934	779 [a]
	(2.461)	(2.346)	(2.413)	(2.413)			
Wealth proxy (cows owned)	1.097	0.896	1.000	1.023	0.262	0.899	779 [a]
	(2.628)	(2.273)	(2.577)	(2.361)			
Visited for usage check	0.083	0.091	0.091	0.083	0.440	0.471	2887
	(0.276)	(0.288)	(0.287)	(0.276)			

Standard deviations reported in parentheses. (a) Variable available only for participants in accompanying methodological study (see Section 2.1.1). (b) A product is "available" in a village if it is "mostly" or "always" available in at least one outlet/drugshop of the village. (c) Reports of free distribution based on village chief's (LC1's) answer to the questions "Has [the product] been distributed for free in the past in this village?" and, if so, "When was the product last distributed for free in this village?", where "yes" is coded as 1 and "no" or "I do not know" are coded 0.

Table 2: Summary Statistics of Respondents' Familiarity with Products

Drug	Percent reporting they recognize a shown drug (1)	Percent of respondents who say they recognize the brand (2)	Percent giving a price estimate (any brand) (3)	Percent giving a price estimate (same brand) (4)	N (5)
Panadol	95.5%	10.2%	87.7%	9.4%	1282
Elyzole	64.4%	7.7%	58.4%	6.5%	1191
Zinkid/ORS	51.4%	5.9%	45.6%	4.5%	1275
Zinkid (lower & upper bound)[a]			16.3%-45.6%	1.3%-4.5%	1275
Aquasafe	71.4%	15.8%	65.7%	14.3%	2019

These data were collected during the Wave 1 by a marketer. Prior to marketing, we asked respondents about the two products that would not later be marketed to them. Column 1 reports answers to the question "Do you recognize this product that I have here? (Briefly describe what the product is, what it does)". Column 3 reports answers to the question, "How much would you expect to pay for this product [there]?". The available choices were: (a) Don't know, (b) It is free, (c) It is sold at this price: UGX_____ (enter amount), (d) I am not certain, but I would estimate this price: UGX_____. (a) Zinkid and ORS were shown as bundle. In order to unbundle familiarity with the two products, we exploited whether respondents gave the price estimate in the unit of sachets or tablets. A respondent giving a price in the unit of sachets is taken to refer to ORS, since Zinkid is distributed in tablets. Since we cannot rule out that people knew both drugs but only reported their perceived price of ORS, this estimate is a lower bound. The upper bounds for familiarity levels with Zinkid are the joint levels presented for Zinkid/ORS.

Table 3: Demand in Wave 1

Product Offered :	Pooled		Panadol[a]		Elyzole[a]		Zinkid[a]	
Dependent Variables:	Take up	Quantity[b]	Take up	Quantity[b]	Take up	Quantity[b]	Take up	Quantity[b]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full sample								
NGO in Wave 1	0.053	0.023	-0.007	-0.136	0.001	0.002	0.159***	0.173***
	(0.033)	(0.064)	(0.038)	(0.145)	(0.045)	(0.061)	(0.044)	(0.049)
Free in Wave 1	0.469***	0.068	0.237***	-0.732***	0.463***	0.233***	0.699***	0.666***
	(0.023)	(0.045)	(0.024)	(0.097)	(0.029)	(0.040)	(0.033)	(0.038)
Free*NGO	-0.054	-0.019	0.011	0.141	-0.007	-0.012	-0.170***	-0.189***
	(0.034)	(0.066)	(0.039)	(0.150)	(0.047)	(0.062)	(0.046)	(0.050)
Constant	N/A[c]	N/A[c]	0.761***	1.826***	0.460***	0.657***	0.276***	0.309***
			(0.025)	(0.122)	(0.046)	(0.058)	(0.040)	(0.047)
Observations	3879	3879	1228	1228	1394	1394	1257	1257
Mean of NGO*Sale	0.580	0.945	0.754	1.599	0.539	0.774	0.460	0.508
Mean of For-Profit*Free	0.999	0.999	0.997	0.997	1.000	1.000	1.000	1.000
Panel B: Households found in both waves								
NGO in Wave 1	0.060*	0.077	0.010	-0.034	-0.008	0.024	0.170***	0.201***
	(0.035)	(0.073)	(0.043)	(0.168)	(0.051)	(0.078)	(0.052)	(0.053)
Free in Wave 1	0.461***	0.070	0.232***	-0.714***	0.443***	0.206***	0.702***	0.686***
	(0.023)	(0.050)	(0.028)	(0.115)	(0.034)	(0.048)	(0.036)	(0.035)
Free*NGO	-0.063*	-0.072	-0.008	0.045	0.002	-0.035	-0.180***	-0.213***
	(0.036)	(0.076)	(0.044)	(0.177)	(0.053)	(0.079)	(0.053)	(0.055)
Constant	N/A[c]	N/A[c]	0.781***	1.863***	0.480***	0.678***	0.281***	0.304***
			(0.040)	(0.167)	(0.049)	(0.064)	(0.046)	(0.050)
Observations	2887	2887	926	926	1027	1027	934	934
Mean of NGO*Sale	0.595	0.996	0.777	1.688	0.548	0.812	0.467	0.515
Mean of For-Profit*Free	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Village assignment to treatment was block randomized according to two variables. The first, price environment, included information about pricing and drug availability with three possible categories: (1) no drug outlets or none of our drugs; (2) no prices above the median or distributed for free; and (3) at least one price above the median. The second, remoteness, also had three categories: (1) easy to travel and close to health center; (2) difficult travel or far from health center; and (3) difficult travel and far from health center. All regressions include controls for stratification cell. Standard errors clustered by village in parentheses. * Denotes significance at the 10-percent level; ** at the 5-percent level; and *** at the 1-percent level. (a) The generic names for the three drugs are: *paracetamol* for Panadol, *albendazole* for Elyzole, *zinc* for Zinkid. (b) The "quantity" dependent variable is the number of units (defined as doses) received or purchased. Respondents in the Free group were offered one unit, respondents in the Sale group were able to purchase up to five units. (c) Includes product-specific intercept.

Table 4: Demand in Wave 2

Product Offered in Wave 2	Pooled	Panadol[a]	Elyzole[a]	Zinkid[a]	Aquasafe[a]
Same As Wave 1?	Same	Same	Same	Same	Different
	(1)	(2)	(3)	(4)	(5)
Panel A: Take-up					
NGO in Wave 1	0.017	0.033	0.027	-0.002	0.054
	(0.032)	(0.040)	(0.056)	(0.051)	(0.059)
Free in Wave 1	-0.100***	-0.116***	-0.118*	-0.052	0.044
	(0.036)	(0.036)	(0.061)	(0.054)	(0.060)
Free*NGO	0.017	0.051	-0.004	-0.002	-0.106
	(0.051)	(0.058)	(0.086)	(0.074)	(0.078)
Constant	N/A[c]	0.862***	0.388***	0.234***	0.457***
		(0.054)	(0.062)	(0.065)	(0.066)
Observations	2150	687	786	677	737
Test of equality of Free coefficient w.r.t.					
Panadol	0.094	N/A	0.980	0.228	0.003
Elyzole	0.208	0.980	N/A	0.325	0.037
Zinkid	0.798	0.228	0.325	N/A	0.176
Mean of NGO*Sale	0.555	0.866	0.521	0.276	0.571
Mean of For-Profit*Free	0.480	0.709	0.379	0.233	0.566
p-value of Free + Free*NGO = 0	0.017	0.131	0.038	0.295	0.216
Effect of Free in specification excluding NGO terms	-0.091***	-0.091***	-0.120***	-0.053	-0.010
	(0.025)	(0.028)	(0.041)	(0.037)	(0.039)
Panel B: Quantity[b]					
NGO in Wave 1	-0.004	-0.086	0.048	0.022	0.052
	(0.069)	(0.172)	(0.096)	(0.059)	(0.092)
Free in Wave 1	-0.214***	-0.429***	-0.154	-0.060	0.101
	(0.073)	(0.151)	(0.097)	(0.057)	(0.111)
Free*NGO	0.110	0.376	-0.056	0.021	-0.176
	(0.114)	(0.237)	(0.138)	(0.095)	(0.142)
Constant	N/A[c]	1.813***	0.510***	0.216***	0.512***
		(0.181)	(0.108)	(0.067)	(0.098)
Observations	2150	687	786	677	737
Test of equality of Free coefficient w.r.t.					
Panadol	0.006	N/A	0.099	0.010	0.000
Elyzole	0.788	0.099	N/A	0.330	0.029
Zinkid	0.258	0.010	0.330	N/A	0.129
Mean of NGO*Sale	0.845	1.720	0.688	0.312	0.714
Mean of For-Profit*Free	0.729	1.363	0.495	0.240	0.762
p-value of Free = 0	0.004	0.005	0.116	0.302	0.367
p-value of Free + Free*NGO = 0	0.198	0.754	0.031	0.607	0.370
Effect of Free in specification excluding NGO terms	-0.157***	-0.240**	-0.182***	-0.047	0.011
	(0.052)	(0.110)	(0.067)	(0.047)	(0.069)

Village assignment to treatment was block randomized according to two variables. The first, *price environment,* included information about pricing and drug availability with three possible categories: (1) no drug outlets or none of our drugs; (2) no prices above the median or distributed for free; and (3) at least one price above the median. The second, *remoteness,* also had three categories: (1) easy to travel and close to health center; (2) difficult travel or far from health center; and (3) difficult travel and far from health center. All regressions include controls for stratification cell. Standard errors clustered by village in parentheses. * Denotes significance at the 10-percent level; ** at the 5-percent level; and *** at the 1-percent level. (a) The generic names for the three drugs are: *paracetamol* for Panadol, *albendazole* for Elyzole, *zinc* for Zinkid, and *sodium dichloroisocyanurate* for Aquasafe. (b) The "quantity" dependent variable is the number of units purchased. (c) Includes product-specific intercept.

Table 5: Observed Usage Summary Statistics

	Conditional on receiving any in Wave 1				% in Sale receiving any in Wave 1	Scaled to include non-takeup in Wave 1		
	Sale	Free	p-value	N	Wave 1	Sale	Free	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of tablets distributed in Wave 1								
Panadol	21.38	10.00	0.00	98	75.2%	16.08	10.00	0.00
Elyzole	8.76	6.00	0.00	84	54.4%	4.77	5.99	0.00
Zinkid & ORS	11.03	10.00	0.12	67	39.2%	4.32	9.97	0.00
Mean tablets remaining from experimental stock								
Panadol	2.53	1.03	0.05	98	75.2%	1.91	1.03	0.17
Elyzole	0.16	0.04	0.43	84	54.4%	0.09	0.04	0.64
Zinkid & ORS	5.34	4.86	0.69	67	39.2%	2.09	4.84	0.00
Proportion of tablets used								
Panadol	0.90	0.90	0.88	98	75.2%	N/A	N/A	N/A
Elyzole	0.99	0.99	0.66	84	54.4%	N/A	N/A	N/A
Zinkid & ORS	0.53	0.51	0.90	67	39.2%	N/A	N/A	N/A
Share of respondents who have positive experimentally provided stock								
Panadol	0.36	0.18	0.05	98	75.2%	0.27	0.18	0.24
Elyzole	0.03	0.02	0.87	84	54.4%	0.01	0.02	0.80
Zinkid & ORS	0.59	0.61	0.88	67	39.2%	0.23	0.60	0.00

Households that did not receive the a product in Wave 1 were not included in the sample for usage checks of experimentally provided product. The share receiving the product in Wave 1 for the Free treatment is approximately 100% for all products. In a previous version of this paper we misreported that 329 individuals were "selected" for usage checks and 251 were "found," implying that "found" refereed to the usage checks. The variable "found" should have indicated "found in Wave 2" and the variable "selected" should have indicated "contacted for usage checks". Because our interest in usage checks is to understand the mechanism behind the Wave 2 results, we restrict the sample frame for analysis to only those individuals reached in Wave 2. Results on the full sample of 329 households reached in the usage checks are statistically identical (results available from the authors on request). We note that the attrition rate of 24% from the usage check to Wave 2 is higher than often found in developing country studies and reflects a deliberate methodological decision to adhere to a more "natural" marketing process, rather than persistently return to households to, in this case, adjudicate their eligibility for a marketing prize. See Section 2 for more discussion of study design and attrition.

A Derivations and proofs

As described in Section 3, the key predictions of the model are all derived from differentiating

$$\begin{aligned}
\pi_t &= \alpha_t E\left(\pi_t | Informed\right) + (1-\alpha_t) E\left(\pi_t | Uninformed\right) \\
&= \alpha_t \Phi\left(\frac{\bar{v}-\tilde{p}_t}{\sigma_I}\right) + (1-\alpha_t)\Phi\left(\frac{\bar{v}+b-\tilde{p}_t}{\sigma_U}\right) \\
&= \alpha_t \Phi\left(\frac{\bar{v}-p_t-R\left(p_t-p_t^r\right)}{\sigma_I}\right) + (1-\alpha_t)\Phi\left(\frac{\bar{v}+b-p_t-R\left(p_t-p_t^r\right)}{\sigma_U}\right)
\end{aligned}$$

with respect to the price in the preceding period. This leads immediately to equation (3):

$$\begin{aligned}
\frac{\partial \pi_2}{\partial p_1} = & \frac{\partial \alpha_2}{\partial p_1}\left[\Phi\left(\frac{\bar{v}-\tilde{p}_2}{\sigma_I}\right) - \Phi\left(\frac{\bar{v}+b-\tilde{p}_2}{\sigma_U}\right)\right] \\
& -\frac{\partial R}{\partial p_1}\left[\frac{\alpha_2}{\sigma_I}\phi\left(\frac{\bar{v}-\tilde{p}_2}{\sigma_I}\right) + \frac{1-\alpha_2}{\sigma_U}\phi\left(\frac{\bar{v}+b-\tilde{p}_2}{\sigma_U}\right)\right].
\end{aligned}$$

We can further expand the first term by noting that α_2, the share informed at the time of the period-2 purchase decision, equals $\alpha_1 + (1-\alpha_1)\Phi\left(\frac{\bar{v}+b-p_1}{\sigma_U}\right)$. Hence, $\partial \alpha_2 / \partial p_1 = -\frac{(1-\alpha_1)}{\sigma_u}\phi\left(\frac{\bar{v}+b-p_1}{\sigma_U}\right) < 0$. The intuition is natural: lowering the price in period 1 increases the share of the population that is informed in period 2.

B Marketing scripts

B.1 Treatment-specific marketing information

- [NGO] UHMG is a Ugandan-based non-governmental organization based in Kampala. UHMG believes that every person in Uganda should have access to affordable health products. UHMG is motivated by the desire to save lives. It is a charity, which means that it makes no profits, and it is funded by international donors.
- [SALE] Today UHMG's beneficiaries are asked to pay a small amount to share the cost of distribution, which allows the good work to be extended to a greater number of needy people.
  - [FREE] Today I am distributing health products for free throughout the village.
- [FOR-PROFIT] Star Pharmaceuticals is a large for-profit company based in Kampala. We sell drugs and health products throughout Uganda. We believe everyone should pay for health products they want, and we believe making profits is a good way to drive progress. We want to become the most successful company in Uganda, and we do this by offering good prices to our customers.
  - [SALE] Today you have the opportunity to buy your normal products at the great prices Star Pharmaceuticals offers, right at your doorstep.
  - [FREE] Today, however, we are distributing our products for free, right at your doorstep, to raise our profile in Gulu.

B.2 Product-specific marketing information

PANADOL

Have you ever returned home from the garden with a pounding headache, or aches in your muscles and joints? Has your child ever woken you in the middle of the night, complaining that their head or stomach is aching? Imagine if one of these things occurred tomorrow, what would you do? You have to run to a drug shop or medical center. But what if that is far away, or there is a long queue, or they are closed or out of stock? That is a bad solution. As both you and I know, one of the best pain killers is Panadol, and yet it is often hard to find. So today, I have Panadol tablets for sale/for free right here! [Take out one unit] I am selling this sheet of 10 tablets for the great price of 500 shillings. I am giving you one sheet of 10 tablets. [Dosage/usage instructions] So, how many sheets will you buy? So, will you accept this product?

ELYZOLE

Do you sometimes drink water that has not been boiled or treated? Do you ever eat fruits directly from the trees, without washing them first? This kind of behavior can lead to worm infections of the stomach. Does anyone in your household ever complain about stomach pains or itchy skin? These are symptoms experienced by someone who has worms. But symptoms often take some time to appear, and so doctors usually advise people to deworm once every three months. The only problem is that it is sometimes hard to access deworming tablets. But today, I have Elyzole deworming tablets for sale/for free right here! [Take out one unit] These three boxes contain a full dose of deworming tablets. There are six tablets in here. These tablets can kill almost all types of worms that can attack humans. I am selling them at the great price of 1500 shillings for one dose of three boxes. I am giving you one dose of three boxes. [Dosage/usage instructions] So, how many full doses do you want to buy? Will you accept this product?

RESTORS & ZINKID

Do you remember a time when your child suffered from diarrhea? Do you remember how weak they became, and how worried that made you? When a child becomes ill with diarrhea, it is important to quickly replenish all the salts and nutrients that they are losing. I'm sure you have heard of oral rehydration salts. Giving these to a sick child is the first stage of combating the effects of diarrhea. So for that, I am selling/giving away Restors - a high quality brand of ORS. The second step is to provide them with zinc supplements which can stop the diarrhea sooner and reduce the chance of diarrhea returning. For that, I have a brand new product, Zinkid, which is to be taken in combination with ORS. Taking these two products together is a great way to reduce the duration and severity of diarrhea in children. Therefore I am selling one strip of 10 Zinkid tablets with one Restors sachet in combination as one item for the great price of , to equip you with the means to combat diarrhea in your children. Therefore I am giving away one strip of 10 Zinkid tablets with one Restors sachet in combination as one item, to equip you with the means to combat diarrhea in your children. [Dosage/usage information] So how many will you buy today? So will you accept this product?

AQUASAFE

Today I am selling Aquasafe – a high quality brand of water treatment right at your door! Often water from wells and boreholes is not suitable for drinking; it can contain harmful bacteria, parasites and other contaminated substances. Drinking this water can cause various illnesses, including diarrhea which can be very damaging for children. I am offering you a simple solution to this problem. Aquasafe is a fast and effective way of purifying your water – you simply add it to a jerry-can of water and in no time it is safe to drink. [Take out one unit] I am selling this sheet of 8 tablets for the great price of 800 shillings. [Dosage/usage instructions] So, how many sheets will you buy?

Wave 2 introduction

Good morning/afternoon! [Generic pleasantries] My name is ____, I am from Surgipharm Uganda Limited. Have you heard of Surgipharm Uganda Limited before? Surgipharm Uganda Limited is a health care company specializing in the importation, exportation, distribution and marketing of pharmaceutical products. We believe everyone should pay for health products they want, and we believe making profits is a good way to drive progress. We want to become the most successful company in Uganda, and we do this by supplying quality goods. I hope you will remember the name of Surgipharm Uganda Limited. [Move on to Aquasafe Price Perception Survey if Aquasafe is not assigned product, then to the sales pitch.]

C Post-Marketing Survey

M A R K E T F E E D B A C K

Intended Respondent's Name: ____ Gender: M F Date of Birth:____________

I met: this person spouse Spouse Name: _________________________ (If spouse was met) Enumerator Name:_________________________

Product: Deworming Panadol ORS/Zinkid Aquasafe Date: Subcounty: Parish: Village:

IN ADDITION TO CIRCLING THE RESPONSE, PLEASE WRITE COMPLETE SENTENCES TO EXPLAIN THE RESPONDENT"S ANSWER MORE THOROUGHLY

Before filling in this form, you must:

1. Introduce yourself, conduct the Price Perception Survey, and deliver the sales pitch.
2. Answer any questions the respondent may ask about the product to the best of your ability.
3. Wait until the respondent has made a decision to purchase or not purchase. If they purchased, any change must be handed over.

Inform the respondent that you would now like to ask them a few brief questions that will help your organization improve in the future. To learn more about why they did or did not buy the product, ask the following questions:

1) Did the respondent make a purchase? Yes No
   If 'Yes' move to Question 2.
   If 'No' move to Question 3.

2) [If they made a purchase] Ask Questions a) to c) below:

   a. Can you tell me more about why you bought this product? *CIRCLE ALL THAT APPLY*
      1---I ran out of my supply ____
      2--- I trust you (*ASK WHY AND WRITE ANSWER OPPOSITE)* ____
      3---The price is cheaper than what I can get it for here ____
      4--- I want to sell it on to others ____
      5--- I would have to travel far to find this elsewhere ____
      6--- I want it in case someone becomes sick ____
      7---Other (FILL IN OPPOSITE)
      99--- Didn't answer

   b. For whom did you buy this for? *CIRCLE ALL THAT APPLY*
      1--- Myself 2--- Adults 3---Grandparents / Elderly
      4---Children/babies 4---Other: ______________________________________
      99-- Didn't answer

   c. When do you expect to start using the product?
      1---This week
      2--- Next week
      3---In the next month
      4---In the next 2-3 months
      5---6 months or more
      6--- Other________________________________
      99—Didn't answer

3) [If did not make a purchase] Can you tell me more about why you did not buy this? *CIRCLE ALL THAT APPLY*
   1--- I got it for free previously, why should I buy it now?
   2--- Other people in this village have previously got it for free.
   3--- I'd like to buy it, but don't have the money here.
   4--- I think it is too expensive.
   5--- It's not essential.
   6--- I already have enough of it.
   99—Didn't answer
   7--- I need to ask my spouse.
   8--- I don't trust you or I'm uncomfortable buying this from you.
   9--- Don't know
   10--- Didn't answer
   11--- Other: ____
   ____

4) [Ask everyone] Is this the type of product that people in your village would resell or trade?
   1---Yes If yes, how much do you think they could sell/trade it for? |_________| UGX --or--- Item to trade with: ____________________
   2---No
   99—Didn't answer

Leave the respondent's home and fill out the Tracking Sheet

Figure A1

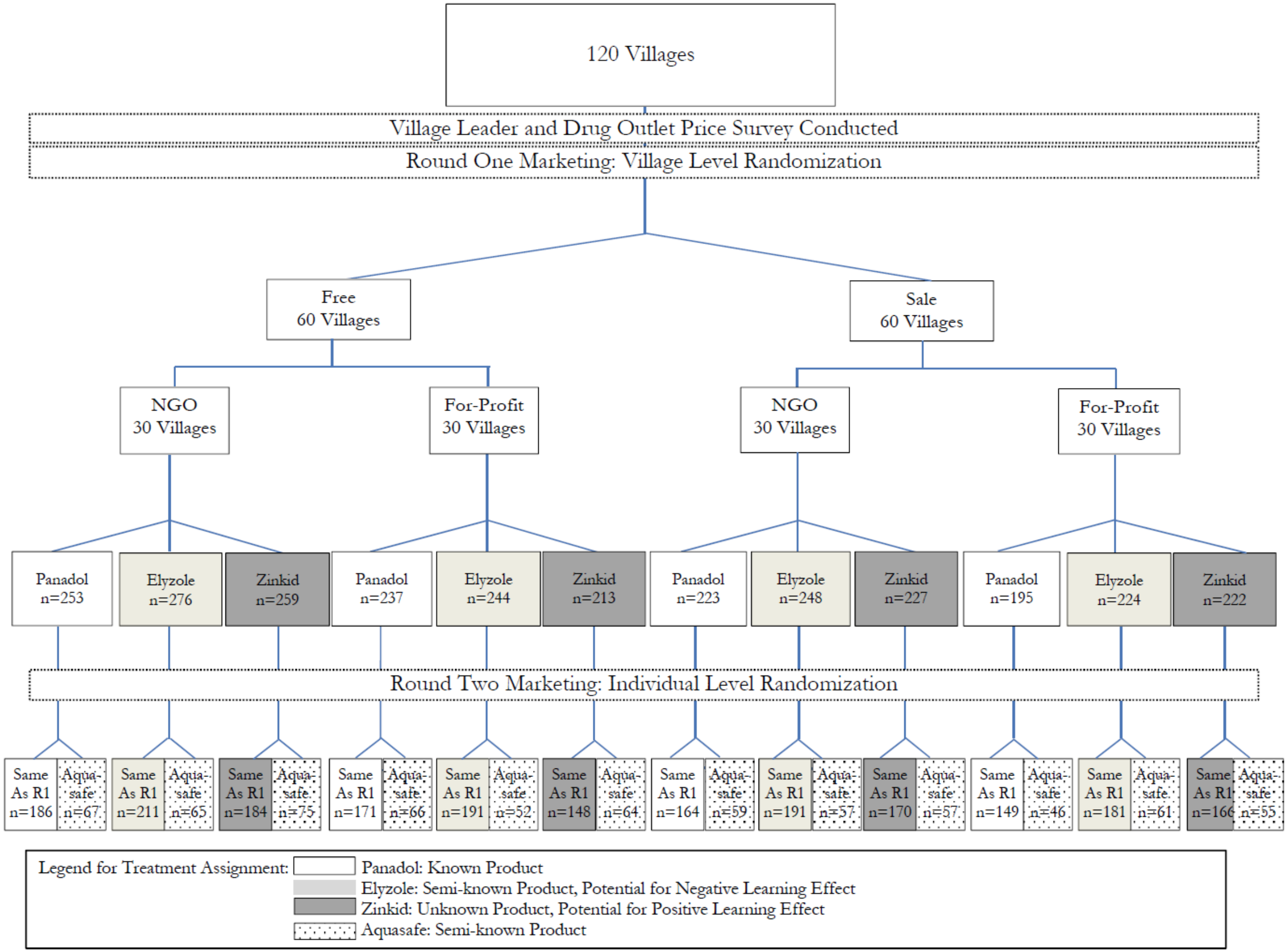

120 Villages
Village Leader and Drug Outlet Price Survey Conducted
Round One Marketing: Village Level Randomization
Free 60 Villages
Sale 60 Villages
NGO 30 Villages
For-Profit 30 Villages
NGO 30 Villages
For-Profit 30 Villages
Panadol n=253
Elyzole n=276
Zinkid n=259
Panadol n=237
Elyzole n=244
Zinkid n=213
Panadol n=223
Elyzole n=248
Zinkid n=227
Panadol n=195
Elyzole n=224
Zinkid n=222
Round Two Marketing: Individual Level Randomization
Same As R1 n=186
Aqua-safe n=67
Same As R1 n=211
Aqua-safe n=65
Same As R1 n=184
Aqua-safe n=75
Same As R1 n=171
Aqua-safe n=66
Same As R1 n=191
Aqua-safe n=52
Same As R1 n=148
Aqua-safe n=64
Same As R1 n=164
Aqua-safe n=59
Same As R1 n=191
Aqua-safe n=57
Same As R1 n=170
Aqua-safe n=57
Same As R1 n=149
Aqua-safe n=46
Same As R1 n=181
Aqua-safe n=61
Same As R1 n=166
Aqua-safe n=55
Legend for Treatment Assignment:
Panadol: Known Product
Elyzole: Semi-known Product, Potential for Negative Learning Effect
Zinkid: Unknown Product, Potential for Positive Learning Effect
Aquasafe: Semi-known Product

Table A1: Entry into Sample & Attrition

	Find Rate Conditional on Row Variable Value		p-value of	
	Yes	No	Diff.	
	(1)	(2)	(3)	
Panel A: Wave 1, Entry into Sample				
N	3,879	1,828		
NGO treatment	0.691	0.669	0.384	a
	(0.462)	(0.471)		
Sale treatment	0.654	0.705	0.040	a
	(0.476)	(0.456)		
Panadol Sale	0.716	0.806	0.000	
	(0.451)	(0.396)		
Elyzole Sale	0.740	0.782	0.039	
	(0.439)	(0.413)		
Zinkid Sale	0.728	0.763	0.096	
	(0.445)	(0.425)		
Female	0.643	0.702	0.000	
	(0.479)	(0.457)		
Village easy to reach and close to health center	0.651	0.699	0.062	a
	(0.477)	(0.459)		
Panel B: Wave 2, Attrition (conditional on entering into sample in Wave 1)				
N	2,887	992		
Received product in wave 1	0.750	0.723	0.281	a
	(0.433)	(0.448)		
NGO treatment	0.765	0.723	0.110	a
	(0.424)	(0.447)		
Sale treatment	0.742	0.747	0.856	a
	(0.438)	(0.435)		
Panadol Sale	0.783	0.765	0.517	
	(0.412)	(0.424)		
Elyzole Sale	0.762	0.755	0.793	
	(0.427)	(0.431)		
Zinkid Sale	0.774	0.741	0.241	
	(0.419)	(0.439)		
Female	0.710	0.783	0.000	
	(0.454)	(0.412)		
Visited for usage check	0.763	0.743	0.418	
	(0.426)	(0.437)		
Panadol available[b]	0.729	0.753	0.378	a
	(0.445)	(0.431)		
Elyzole available[b]	0.742	0.745	0.921	a
	(0.438)	(0.436)		
Zinkid available[b]	0.745	0.744	0.985	a
	(0.437)	(0.436)		
Reports free distribution of any drug in last 3 mo.	0.760	0.729	0.221	a
	(0.427)	(0.445)		
Village easy to reach and close to health center	0.734	0.751	0.524	a
	(0.442)	(0.433)		

Standard deviations reported in parentheses. (a) p-value of differences adjusted for clustering at the village level (b) A product is "available" in a village if it is "mostly" or "always" available in at least one outlet/drugshop of the village. (c) Reports of free distribution based on village chief's (LC1's) answer to the questions "Has [the product] been distributed for free in the past in this village?" and, if so, "When was the product last distributed for free in this village?", where "yes" is coded as 1 and "no" or "I do not know" are coded 0.

Table A2: Prior Free Distribution Summary Statistics

Time since last free distribution (percent)	Panadol	Deworming	ORS	Condoms	Any*
In past month	1	21	2	5	26
1-3 months ago	0	26	1	1	27
3-6 months ago	0	11	1	3	13
6-12 months ago	0	11	3	3	17
More than 1 year ago	0	3	8	4	14
Cumulative; Any distributions in prior period (percent)					
	Panadol	Deworming	ORS	Condoms	Any*
In past month	1	21	2	5	26
0-3 months ago	1	47	3	6	49
0-6 months ago	1	58	3	8	59
0-12 months ago	1	69	7	12	73
Ever	1	72	15	16	77

Total sample size is 120 villages. Three had missing observations in deworming questions and are dropped from sample. * Any free drug is indicator, equal to 1 if any of Panadol, deworming, ORS, or condoms have previously been distributed for free in the village. No village had ever received prior free distributions of Zinkid or Restors.

Table A3: Heterogeneous efffects with respect to price index

Product Offered in Wave 2	Pooled		Panadol		Elyzole		Zinkid		Aquasafe	
Same As Wave 1?	Same		Same		Same		Same		Different	
Dependent Variables:	Take up	Quantity	Take up	Quantity	Take up	Quantity	Take up	Quantity	Take up	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temp Panel: using productAssignedInitial2										
NGO in Wave 1	0.009	-0.026	0.056	-0.061	-0.002	0.000	-0.014	-0.002	0.023	-0.002
	(0.041)	(0.075)	(0.045)	(0.182)	(0.065)	(0.108)	(0.060)	(0.070)	(0.064)	(0.104)
Free in Wave 1	-0.105**	-0.214***	-0.100**	-0.394**	-0.126*	-0.171*	-0.072	-0.077	0.006	0.039
	(0.041)	(0.077)	(0.044)	(0.170)	(0.065)	(0.103)	(0.061)	(0.067)	(0.061)	(0.124)
Free*NGO	0.025	0.158	0.033	0.437*	0.029	0.017	0.000	0.027	-0.074	-0.107
	(0.053)	(0.114)	(0.062)	(0.243)	(0.087)	(0.138)	(0.077)	(0.101)	(0.079)	(0.143)
High price index	-0.004	0.110	0.114	0.489	0.002	-0.006	-0.116	-0.124	-0.086	-0.242
	(0.069)	(0.162)	(0.077)	(0.354)	(0.126)	(0.197)	(0.104)	(0.131)	(0.112)	(0.176)
High price*Free in Wave 1	-0.026	-0.141	-0.066	-0.326	-0.055	-0.098	0.051	0.031	0.121	0.158
	(0.054)	(0.122)	(0.078)	(0.283)	(0.105)	(0.138)	(0.096)	(0.143)	(0.092)	(0.121)
High price*NGO	0.003	-0.106***	-0.065	-0.358	0.012	-0.071	0.043	0.096***	0.015	0.017***
	(0.259)	(0.014)	(0.076)	(0.285)	(0.738)	(0.135)	(0.428)	(0.016)	(0.009)	(0.001)
Constant	0.168	0.730***	0.738*	0.135***	0.523	0.672***	0.338***	0.245**	0.028	0.039
	(0.838)	(0.188)	(0.428)	(0.016)	(0.338)	(0.245)	(0.105)	(0.122)	(0.179)	(0.227)
Observations	2034	2034	643	643	751	751	640	640	695	695
Test of equality of Free coefficient w.r.t.										
Panadol	0.195	0.268	N/A	N/A	0.000	0.000	0.000	0.000	0.000	0.000
Elyzole	0.000	0.000	0.000	0.000	N/A	N/A	0.000	0.000	0.000	0.000
Zinkid	0.000	0.000	0.000	0.000	0.000	0.000	N/A	N/A	0.000	0.000
Mean of NGO*Sale	0.551	0.827	0.870	1.701	0.511	0.661	0.280	0.317	0.562	0.691
Mean of For-Profit*Free	0.477	0.732	0.708	1.380	0.377	0.497	0.229	0.236	0.564	0.762
p-value of Free = 0	0.012	0.006	0.024	0.022	0.053	0.099	0.244	0.252	0.920	0.755
p-value of Free + Free*NGO = 0	0.056	0.536	0.141	0.813	0.151	0.161	0.203	0.525	0.246	0.496

High price indicates at least one drug price above the median. The generic names for all four drugs are: *paracetamol* for Panadol, *albendazole* for Elyzole, *zinc* for Zinkid, and *sodium dichloroisocyanurate* for Aquasafe. The "quantity" dependent variable is the number of units (defined as doses) received or purchased. Respondents in the Free group were offered one unit, respondents in the Sale group were able to purchase up to five units. Pooled regression includes product-specific intercepts and only those households offered the same product in both waves. Village assignment to treatment was block randomized according to two variables. The first, price environment, included information about pricing and drug availability with three possible categories: (1) no drug outlets or none of our drugs; (2) no prices above the median or distributed for free; and (3) at least one price above the median. The second, remoteness, also had three categories: (1) easy to travel and close to health center; (2) difficult travel or far from health center; and (3) difficult travel and far from health center. All regressions include controls for stratification cell. Standard errors clustered by village in parentheses. * Denotes significance at the 10-percent level; ** at the 5-percent level; and *** at the 1-percent level.

Table A4: Heterogeneous efffects with respect to remoteness

Product Offered in Wave 2	Pooled		Panadol		Elyzole		Zinkid		Aquasafe	
Same As Wave 1?	Same		Same		Same		Same		Different	
Dependent Variables:	Take up	Quantity	Take up	Quantity	Take up	Quantity	Take up	Quantity	Take up	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temp Panel: using productAssignedInitial2										
NGO in Wave 1	0.017	-0.071	0.096	-0.080	-0.024	-0.130	-0.011	0.019	-0.010	-0.049
	(0.051)	(0.103)	(0.060)	(0.244)	(0.080)	(0.125)	(0.082)	(0.098)	(0.080)	(0.130)
Free in Wave 1	-0.089*	-0.239**	-0.067	-0.548**	-0.164**	-0.153	-0.019	-0.026	0.073	0.061
	(0.049)	(0.102)	(0.056)	(0.215)	(0.074)	(0.132)	(0.078)	(0.089)	(0.073)	(0.120)
Free*NGO	0.023	0.126	0.045	0.388*	0.006	-0.033	0.010	0.036	-0.085	-0.134
	(0.051)	(0.107)	(0.056)	(0.220)	(0.083)	(0.133)	(0.075)	(0.095)	(0.078)	(0.138)
Remote	0.024	-0.054	0.058	-0.130	-0.031	-0.083	0.055	0.071	0.048	0.051
	(0.047)	(0.094)	(0.049)	(0.212)	(0.075)	(0.125)	(0.075)	(0.083)	(0.074)	(0.115)
Remote*Free in Wave 1	-0.025	0.031	-0.089	0.179	0.067	0.001	-0.063	-0.066	-0.050	0.034
	(0.052)	(0.106)	(0.060)	(0.231)	(0.083)	(0.133)	(0.079)	(0.099)	(0.081)	(0.134)
Remote*NGO	-0.008	0.095	-0.104*	0.011	0.073	0.252*	-0.008	-0.020	0.084	0.133
	(0.052)	(0.107)	(0.060)	(0.231)	(0.082)	(0.133)	(0.080)	(0.098)	(0.081)	(0.137)
Constant	0.848***	1.842***	0.868***	2.138***	0.545***	0.775***	0.224**	0.195*	0.585***	0.785***
	(0.054)	(0.121)	(0.056)	(0.226)	(0.084)	(0.142)	(0.091)	(0.105)	(0.074)	(0.126)
Observations	2150	2150	687	687	786	786	677	677	737	737
Test of equality of Free coefficient w.r.t.										
Panadol	0.197	0.268	N/A	N/A	0.000	0.000	0.000	0.000	0.000	0.000
Elyzole	0.000	0.000	0.000	0.000	N/A	N/A	0.000	0.000	0.000	0.000
Zinkid	0.000	0.000	0.000	0.000	0.000	0.000	N/A	N/A	0.000	0.000
Mean of NGO*Sale	0.555	0.845	0.866	1.720	0.521	0.688	0.276	0.312	0.571	0.714
Mean of For-Profit*Free	0.480	0.729	0.709	1.363	0.379	0.495	0.233	0.240	0.566	0.762
p-value of Free = 0	0.072	0.021	0.233	0.012	0.028	0.250	0.804	0.771	0.316	0.614
p-value of Free + Free*NGO = 0	0.147	0.203	0.704	0.459	0.038	0.085	0.892	0.917	0.881	0.545

Remote indicates village is both difficult to reach and far from the nearest health center. The generic names for all four drugs are: *paracetamol* for Panadol, *albendazole* for Elyzole, *zinc* for Zinkid, and *sodium dichloroisocyanurate* for Aquasafe. The "quantity" dependent variable is the number of units (defined as doses) received or purchased. Respondents in the Free group were offered one unit, respondents in the Sale group were able to purchase up to five units. Pooled regression includes product-specific intercepts and only those households offered the same product in both waves. Village assignment to treatment was block randomized according to two variables. The first, price environment, included information about pricing and drug availability with three possible categories: (1) no drug outlets or none of our drugs; (2) no prices above the median or distributed for free; and (3) at least one price above the median. The second, remoteness, also had three categories: (1) easy to travel and close to health center; (2) difficult travel or far from health center; and (3) difficult travel and far from health center. All regressions include controls for stratification cell. Standard errors clustered by village in parentheses. * Denotes significance at the 10-percent level; ** at the 5-percent level; and *** at the 1-percent level.

Table A5: Heterogeneous efffects with respect to prior free distributions

Product Offered in Wave 2	Pooled		Panadol		Elyzole		Zinkid		Aquasafe	
Same As Wave 1?	Same		Same		Same		Same		Different	
Dependent Variables:	Take up	Quantity	Take up	Quantity	Take up	Quantity	Take up	Quantity	Take up	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temp Panel: using productAssignedInitial2										
NGO in Wave 1	0.016	0.007	0.051	0.002	0.021	0.037	-0.019	-0.005	0.066	0.018
	(0.042)	(0.080)	(0.049)	(0.174)	(0.078)	(0.128)	(0.058)	(0.069)	(0.070)	(0.112)
Free in Wave 1	-0.075	-0.207**	-0.076	-0.369*	-0.110	-0.191	-0.023	-0.046	0.038	0.106
	(0.046)	(0.091)	(0.048)	(0.196)	(0.084)	(0.125)	(0.065)	(0.073)	(0.068)	(0.145)
Free*NGO	0.012	0.102	0.055	0.339	-0.010	-0.029	-0.019	-0.002	-0.070	-0.115
	(0.049)	(0.099)	(0.056)	(0.234)	(0.084)	(0.131)	(0.073)	(0.090)	(0.078)	(0.135)
Free distribution of any drug	0.035	0.070	0.026	0.198	0.028	0.005	0.057	0.048	0.012	-0.018
in past three months	(0.042)	(0.080)	(0.045)	(0.196)	(0.074)	(0.119)	(0.064)	(0.072)	(0.073)	(0.113)
Prior free distribution*Free in Wave 1	-0.054	-0.020	-0.082	-0.099	-0.020	0.049	-0.063	-0.031	0.001	-0.060
	(0.050)	(0.101)	(0.054)	(0.231)	(0.085)	(0.132)	(0.075)	(0.091)	(0.081)	(0.146)
Prior free distribution*NGO	0.017	-0.003	-0.035	-0.089	0.019	-0.023	0.059	0.079	-0.065	-0.004
	(0.048)	(0.096)	(0.056)	(0.227)	(0.083)	(0.130)	(0.075)	(0.093)	(0.081)	(0.145)
Constant	0.844***	1.769***	0.931***	1.998***	0.483***	0.678***	0.201**	0.197**	0.545***	0.647***
	(0.058)	(0.118)	(0.069)	(0.220)	(0.100)	(0.158)	(0.079)	(0.087)	(0.093)	(0.139)
Observations	2150	2150	687	687	786	786	677	677	737	737
Test of equality of Free coefficient w.r.t.										
Panadol	0.198	0.268	N/A	N/A	0.930	0.131	0.296	0.017	0.003	0.001
Elyzole	0.000	0.000	0.000	0.000	N/A	N/A	0.000	0.000	0.000	0.000
Zinkid	0.119	0.012	0.000	0.000	0.930	0.131	N/A	N/A	0.003	0.001
Mean of NGO*Sale	0.555	0.845	0.866	1.720	0.521	0.688	0.276	0.312	0.571	0.714
Mean of For-Profit*Free	0.480	0.729	0.709	1.363	0.379	0.495	0.233	0.240	0.566	0.762
p-value of Free = 0	0.107	0.025	0.117	0.062	0.190	0.129	0.729	0.533	0.577	0.466
p-value of Free + Free*NGO = 0	0.091	0.200	0.675	0.878	0.067	0.036	0.481	0.496	0.645	0.935

The generic names for all four drugs are: *paracetamol* for Panadol, *albendazole* for Elyzole, *zinc* for Zinkid, and *sodium dichloroisocyanurate* for Aquasafe. The "quantity" dependent variable is the number of units (defined as doses) received or purchased. Respondents in the Free group were offered one unit, respondents in the Sale group were able to purchase up to five units. Pooled regression includes product-specific intercepts and only those households offered the same product in both waves. Village assignment to treatment was block randomized according to two variables. The first, price environment, included information about pricing and drug availability with three possible categories: (1) no drug outlets or none of our drugs; (2) no prices above the median or distributed for free; and (3) at least one price above the median. The second, remoteness, also had three categories: (1) easy to travel and close to health center; (2) difficult travel or far from health center; and (3) difficult travel and far from health center. All regressions include controls for stratification cell. Standard errors clustered by village in parentheses. * Denotes significance at the 10-percent level; ** at the 5-percent level; and *** at the 1-percent level.