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

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Abstract

Pricing policy for any experience good faces a key tradeoff. On one hand, a price reduction increases immediate demand and hence more people learn about the product. On the other hand, lower prices may serve as price anchors and, through a comparison effect, decrease subsequent demand. This tension is particularly important for the distribution of health products in low-income countries, where free or heavily subsidized distribution is a common but controversial practice. Based on a model combining the learning aspect of experience goods with reference-dependent preferences, we setup a field experiment in Northern Uganda in which three health products differing in their scope for learning were initially offered either for free or for sale at market prices. In line with prior studies, when the product has potential for positive learning, we do not find an effect of free distribution on future demand. However, for products without scope for positive learning, we find evidence of price anchors: future demand is lower after a free distribution than after a distribution at market prices.

JEL: D11, D12, D83, I11, I18, O12

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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] In contrast, a number of recent field experiments, particular those related to the hotly contested issue of pricing health goods in low-income countries, find no evidence for such non-budget-constraint effects of prices on demand and usage.[3] Reconciling these two seemingly divergent sets of findings has implications for many questions of pricing policy. 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—may explain some of these differences and provide a fuller understanding of how current prices shape future demand.

[1] In psychology, there is a long history of studying the effect of reference points in absolute judgments. See, for example, 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] 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), Ashraf et al. (2010), and Dupas (2014), discussed below. 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.

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' 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 the product's intrinsic value. We aim to test for the presence of such price anchors and examine their interaction with the scope for learning about a product's value.

We first develop a simple model of purchase decisions that combines the learning aspect of experience goods with reference-dependent preferences. The model frames several predictions about the effect of price anchors and how they may interact with the potential for learning about experience goods with different degrees of uncertainty or potential biases in beliefs about the product's value. In aiming to clearly 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.

Using this theoretical framework, we designed a field experiment in northern Uganda where health products were distributed door-to-door either for free or for sale at market prices. By design, we offered three products that differed in their scope for learning: Panadol, a pain reliever widely known to consumers and for which we expect no scope for learning; Elyzole, a deworming drug that was moderately well-known and for which we expect negative learning due to side effects; and Zinkid, an improved treatment for childhood diarrhea that was largely unknown and for which

we expect positive learning. Approximately ten weeks later, representatives from a third organization offered the households either the same or a new health product for sale at market prices. Our key outcome measure is the purchase rate in this second wave.

The tension between learning and price anchors is particularly important for the distribution of health products in low-income countries, where free or heavily subsidized distribution is a common but controversial practice. 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. As such, they have been much studied in the recent empirical literature on the dynamic pricing of experience goods. 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. Moreover, distribution and pricing policies for health goods are important policy questions, making this a natural setting in which to build experimental evidence.

We find evidence supporting the presence of price anchors, consistent with models of reference-dependent preferences (Kőszegi and Rabin, 2006) where comparison effects dominate. For the well-known product with little scope for learning, Panadol, demand in the subsequent sale is nearly 12 percentage points lower for those who were previous offered the product for free relative to those who were offered the product at market prices. 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 don't want to purchase the product because they or someone in their community had received it for free in the past.

As predicted by the theory, the relative reduction in demand is even larger when there was scope for negative learning about the product (Elyzole) and less negative when there was scope for positive learning (Zinkid). In the latter case, demand following the free distribution is marginally lower than after the sale distribution, but the difference is not statistically distinguishable from zero.

we do not observe a statistically significant reduction in demand following the free distribution. The pattern of effects is consistent with the theoretical prediction that any negative demand effects from price anchoring can be opposed or even reversed by the potential for positive learning; however, we note that none of the differences across products are statistically significant at conventional levels.[4]

To test auxiliary hypotheses about the mechanism 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. Our hypothesis was that the type of distributing organization would affect how individuals updated their beliefs about prices and product quality. 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 attempting to increase exposure to its products 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 that the shift in price reference point differs according to the distributor's identity. Relative to a sale distribution, free distribution by a for-profit entity lowers subsequent demand by the same amount

[4]We view this as support for the conclusions of Cohen and Dupas (2010) and Dupas (2014). As discussed in the latter, there is potential for substantial income effects in the case of insecticide-treated bednets. The use of bednets may reduce the incidence of malaria thus increasing households' income and in turn, future demand for additional bed nets. 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.

as free distribution by a non-profit. However, we find that for the relatively unknown product (Zinkid), households are 52% more likely to purchase 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. This finding that NGOs are more effective at stimulating demand for unknown products should be interpreted with caution. It 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 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 our experiment's ability to test this hypothesis was relatively underpowered due to budgetary constraints, and the confidence intervals for the cross-product effect are largely uninformative.

This paper contributes to three distinct strands of research. First, it provides additional evidence for the importance of price anchors in an important, non-laboratory domain of economic behavior. Second, it builds 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. This mechanism may be particularly important in the case of pharmaceutical demand (Crawford and Shum, 2005).

Third, our study informs 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 (Kremer and Miguel, 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). This debate has been at the center of many discussions on development. Sachs (2005) makes a strong moral argument in favor of national strategies to provide free distribution of health products. At the same time, many countries worry that free distribution could undermine the incentives for burgeoning commercial markets to deliver these products consistently and cheaply (Roberts 2007; Easterly 2006).

We stress that taking policy implications from our findings requires a number of assumptions about context and objectives that are beyond the scope of this paper. However, while context and product characteristics may differ greatly and while governments, firms and other organizations may have very different objective functions when considering the optimal way to distribute products, the tension between price anchors and learning is likely to be an important input in most cases.

2 Experimental Design & Data

2.1 Experimental Design

2.1.1 Setting and sampling

We conducted our experiment in Gulu District in northern Uganda, an area destabilized by an insurgency from 1987 until 2006. The majority of the population was forced to live in Internal Displacement camps and only returned between 2006 and

2009 to their villages.[5] 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 or other areas where the delivery of health goods is a primary policy concern, 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.[6] 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. Further work is required to say definitively how our results would generalize to other settings.[7]

We selected 120 villages for the study[8] and from each of these villages randomly selected approximately 50 households from the household list kept by the village chief.[9] On average, our sample included 47.6 households per village. Within each

[5]See Joireman et al. (2012) for details on the conflict and patterns of resettlement.

[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" (CKW's), local community members hired by Grameen Foundation to both disseminate and collect information.

[7]As described below, we test for treatment effect heterogeneity with respect to prior free distributions, but the confidence intervals are large and the results inconclusive.

[8]Of these 120 villages, 72 were villages participating in a 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.

[9]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 bednets, 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. The village lists contain one household per page. Field staff were provided with lists of randomly generated numbers, which were used to select random households from the lists. Further, field staff were provided with a list of respondent names from the methodological study in the respective village, which they included discreetly in the list of randomly drawn households in order not to raise suspicion why specific people were targeted. In Uganda, the village chief is referred to as Local Council 1 Chairperson ("LC1").

village, respondent households were divided geographically into three clusters and each cluster assigned to a marketer.[10]

2.1.2 First Wave of Marketing

Figure 1 summarizes the experimental design. The first wave of marketing 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. 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. The village treatment assignment was stratified by health good prices, remoteness of the village, distance to the nearest health center and whether there had been prior free distribution of health goods.[11] 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[12] (albendazole, deworming medication), and a combination pack of Restors (oral rehydration salts, "ORS") and Zinkid (zinc supplements). For the Sale treatment group, we used

[10]Clustering was done based on logistical ease. Clusters were not always of equal size, but rather divided to minimize distances between respondents for each marketer.

[11]Remoteness was ranked by team leaders on a seven-point scale. To reduce the number of cells, stratification variables 1 & 2 and 3 & 4 were collapsed into a single dimension, respectively. Each stratification variable had three categories. The variable 'new price index' has the values: 1 "no drug shop or none of our drugs", 2 "no prices above median or distributed free", and 3 "at least one price above median". The variable remote has the values: 1 "easy to travel and close to health center", 2 "not easy to travel or far from health center", and 3 "not easy to travel and far from health center."

[12]Elyzole, the drug we used in this study, is manufactured by Elys Chemical Industries, Ltd., a Kenyan pharmaceutical manufacturing firm, and is registered with the National Drug Authority of Uganda. Also available for sale in Uganda is "elyzol", a different drug that is used for a variety of infections but not intestinal worms. This drug is not registered in Uganda for distribution or sale with the National Drug Authority.

the same price for the entire study, regardless of village. We set the price for the Sale group to be slightly above the average market price in order to minimize the chance that respondents were purchasing only in order to resell.[13]

In order to maximize the likelihood that individuals perceived the various marketing and sales interactions as natural rather than experimental artifacts, we worked 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 ourselves 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 between marketers and respondents.[14]

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 any very short-term liquidity constraints. In order to minimize any differential response rates, a similar flyer was distributed in the Free treatment arm announcing a "distribution" but not detailing whether products would be sold or distributed for free.

[13]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.

[14]More than 80% of the population of Gulu District is of the Acholi ethnic group, and most inhabitants speak the Acholi dialect of Luo.

Marketers delivered product- and entity-specific sales pitches and answered any questions about the product. The treatment-specific marketing scripts are provided in Appendix B.1. Marketing pitches also contained product-specific information, including medical guidelines concerning usage and dosage, which are detailed in Appendix B.2. A pharmacist trained the marketers on how to explain these usage and dosage guidelines.[15] Respondents were not informed that marketers were selling a variety of products, and the intended impression was that the marketed product was the only product the marketer was selling in order to avoid requests for other products.

In the first wave, we offered the Free treatment arm one unit and the Sale treatment arm a maximum of five units of the assigned product.[16] Prices were non-negotiable. Once this transaction had been completed, marketers would administer a market feedback questionnaire to respondents in the Sale treatment group about why they had decided to buy or not to buy, and who might use the product.[17] In all cases, marketers had only one day to reach all respondents in each village, thus we only reached 74% of the households approached in Wave 1 again in Wave 2. Marketing was not be continued on a second day in order to reduce the possibility of spillovers of information or expectations across respondents. Out of the original 5,708 households identified to be in the study, 3,884 were found in this first wave of marketing.[18]

[15] At the time of purchase or when asking questions, marketers gave respondents information on dosage, storage and recommended use of the respective product. 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. It was given in both verbal and written form in the local language, Acholi.

[16] 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% of households in the Sale treatment purchased five units, suggesting that the cap on the quantity of units for sale was only very rarely, if ever, binding.

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

[18] Note that we do have statistically significant differential attrition between the NGO and for-

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%) although only few with the brand itself (10%).[19] Panadol is also 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 of the relative salience of side-effects and perceived benefits, we expected that any learning effects would be negative (Kremer and Miguel, 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, the generic version (ORS) was widely used and recognized, and freely available from health centers. However, the importance of zinc supplements in combating diarrhea had only recently been established in the global health literature.[20] As such, Zinkid represents a completely new brand and product for which we expect there to be scope for positive learning.[21] Table 2 presents descriptive results from the price perception and product awareness survey.

profit group but not between the sale and free distribution group. This differential attrition will weaken the conclusions we are able to make comparing non-profit and for-profit distribution.

[19]This is likely because the generic unbranded version of Panadol is most commonly purchased.

[20]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 (USAID, 2010; Sanders et al., 2013).

[21]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.

2.1.3 Second Wave of Marketing

We conducted the second wave of marketing on average ten weeks after the first wave.[22] The sole purpose of the second wave 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").[23] Again, marketers were employed by the partner, but recruited, trained and monitored by the study team. In order to reduce association between the first and second waves, we changed the wording of all scripts without significantly affecting the content.[24] We also assigned marketers to villages such that individual marketers did not visit the same village twice in order to reduce the probability that respondents associate the first wave of monitoring with the second wave. While there may be time trends in the demand for health products, we do not believe there is any reason to expect any seasonal fluctuations in demand to vary according to treatment status.[25]

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% 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

[22]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.

[23]The largest pharmaceutical company in Uganda, based in Kampala. Largely similar to Star Pharmaceuticals Ltd., except that it also operates in Kenya.

[24]The marketing script for Wave 2 is included in Appendix B.

[25]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 national clinical guidelines from the Ugandan Ministry of Health suggest preventative deworming of children every three to six months, so we would expect participants would have reasons to demand more deworming medication at the time of our second visit (Ministry of Health, Republic of Uganda, 2012). Evidence suggests that childhood diarrhea is more common during the rainy season because of greater exposure to bacteria (Ahmed et al., 2008), therefore we might expect higher demand for Zinkid to treat diarrhea in wave 1.

one of the two leading brands for water purification, the name itself was not well known by respondents (only 16% recognized the brand, as represented 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".[26] In the second marketing wave, the only randomization was the household-level assignment of the product: 25% of households were marketed the new product, Aquasafe, and 75% were marketed the same health product they were offered during the first marketing wave.

2.2 Data

2.2.1 Village and Drug Outlet Data

Before the first marketing wave, we conducted a survey of community leaders about prior distribution in the village and a survey at the facility level (including both private drug shop and local health clinics). 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. Furthermore, village chiefs were asked about any recent free distributions of health products. We then visited every drug outlet in each village, and asked owners or shop attendants a set of questions about a list of common drugs, including the price each product was sold at, its availability, and the preferred brand in that outlet. 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

[26] 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).

relevant "market price" for the drugs we were selling and to test for treatment effect heterogeneity with respect to market prices and prior exposure to free distributions.

2.2.2 Price Perception Survey

Immediately prior to the sales pitch, marketers administered a price perception survey to 50% 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 the first marketing wave, individuals were asked their price perceptions of the three goods distributed in the wave. In the second marketing wave individuals were asked only about the product added to this wave, Aquasafe.

2.2.3 Post Marketing Survey

In order to understand the determinants of decisions about whether to purchase health products we conducted a short survey for all individuals who received a marketing campaign where products were sold (individuals assigned to the sale group in the first wave and all individuals in the second wave). The purpose of this survey was to mimic traditional "marketing research" in order to ensure that participants' experience was as natural as possible. The survey asked respondents in an unprompted way to explain why they did or did not purchase the product. Responses were later coded into categories representing common responses. The survey is included in Appendix C.

2.2.4 Observational usage data from physical observation of packaging

In order to capture data on product usage, we implemented an incentive compatible mechanism for eliciting patterns in product usage. During the first marketing wave, 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 the first marketing wave (and thus two to four weeks before the second), surveyors made unannounced visits to a randomly selected sample comprising 15% of respondents. At the household, surveyors asked to see blister packs that respondents had received from the Wave 1 marketer, which allowed enumerators to count and record how many tablets were remaining in the blister packs.[27] If respondents produced the correct packaging, they were given three bags of salt as their lottery prize.

3 Theoretical framework

We put forward a model of households' decisions to purchase 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 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

[27] 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 the first wave had been discretely marked so that they could be identified as packaging distributed by our marketers, rather than the same product obtained from elsewhere.

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

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

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). 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 a 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". 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 a household 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, $\tilde{v}_{it} = \bar{v} + b_{it}$, where $b_{it} \sim N(b, \sigma_b^2)$ and b captures the mean bias in the population.[28] 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.[29] For informed households, $v_{it} = v_i$, i.e., the true value. For uninformed households, $v_{it} = \bar{v} + b + \sigma_{itb}$. 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:[30]

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

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

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

[29] For example, evidence from Das et al. (2008) suggests households are willing to pay substantial out of pocket costs for medical "treatments" with no proven benefits that are provided by untrained traditional medical practitioners, suggesting the presence of overly optimistic beliefs about these treatments. In other work, Salmon et al. (2009) show that many parents have overly pessimistic biases about vaccines.

[30] 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 to 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.

lated simply as:

$$\begin{aligned} E\left(\pi_t|\, Informed\right) &= Pr(v_i > \varepsilon_{it} + \tilde{p}_t) \\ &= Pr(\bar{v} + \sigma_{iv} - \varepsilon_{it} > \tilde{p}_t) \\ &= 1 - \Phi\left(\frac{\tilde{p}_t - \bar{v}}{\sigma_I}\right) \\ &= \Phi\left(\frac{\bar{v} - \tilde{p}_t}{\sigma_I}\right), \end{aligned}$$

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:

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

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 $\sigma_U^2 > \sigma_I^2$.[31]

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:

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

[31] 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.

The first term on the right-hand side of (3) is the information effect. It can be either positive 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 hypotheses 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 $E\left(\pi_2 | Informed, \tilde{p}_2\right) > E\left(\pi_2 | Uninformed, \tilde{p}_2\right)$, 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 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 $E\left(\pi_2 | Informed, \tilde{p}_2\right) < E\left(\pi_2 | Uninformed, \tilde{p}_2\right)$, 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 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 pessimistic 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 positive (less 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.[32]

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, any potential increase in future demand is opposed by the price anchoring effect, which can depress demand across the entire population.

4 Results

Following the framework described in Section 3, we posit that in our setting free health goods can affect demand through two different mechanisms: price anchoring

[32] It is worth reiterating at this point that we are making only a positive statement about the effect of free distribution on subsequent demand. As described in the introduction, there are many other reasons to consider the free distribution of deworming medicine and other health products.

and learning. As detailed in Section 2.1, the study 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 type of product a household was offered. Price and type of distributing organization were randomly assigned at the village level, while the product type was assigned at the household level. We run the basic specification

$$y_{ijt} = \beta_0 + \beta_1 NGO_{ij} + \beta_2 Free_{ij} + \beta_3 Free_{ij} \times NGO_{ij} + \gamma X_{ij} + \varepsilon_{ijt}, \qquad (4)$$

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 a 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 of the two stratification variables: a price index and a remoteness index.[33] ε_{ijt} represents the idiosyncratic error, which we cluster at the

[33]Village assignment to treatment groups was stratified on the following two variables: The variable 'price index', which takes the values: 1 "no drug shop or none of our drugs", 2 "no prices above median or distributed free", and 3 "at least one price above median", and the variable 'remoteness index' which takes on the values: 1 "easy to travel and close to health center", 2 "not easy to travel or far from health center", and 3 "not easy to travel and far from health center". These two variables yield nine cells for stratification purposes. They are based on the four variables: First, data on drug shop prices (no data/drug shop, above or at median price, below), second, a seven-point remoteness index (above/below the median), third, distance to the next health center (above/below the median), and fourth, whether there had been a recent distribution of drugs, as reported by the village chief. To reduce the number of cells, stratification variables 1 & 2 and 3 & 4 were collapsed into a single dimension, respectively. Using the four raw variables would have generated cells too small for stratification purposes.

village level, the level of randomization. We split samples to look at different effects by assigned product type.

4.1 Take up in Wave 1

This section describes the effects of prices and distributor identity on contemporaneous demand. Table 3 shows the results, by product, from estimating equation (4). 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.[34]

Unsurprisingly, take up was indeed 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 43.5 percentage points for Elyzole, 23.4 percentage points for Panadol, and 68.6 percentage points for Zinkid. All coefficients are statistically significant a p-values below 0.01.[35]

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 average quantity of Panadol obtained by those in the Sale treatment is 0.721 units (or 42%) higher than for those in the Free treatment. As described in Section 2.1.2, households in the Sale treatment could purchase up to five units

[34]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 with one sachet of oral rehydration salts.

[35]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. Results available on request.

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 15.3 percentage point increase in take up and a 60.3% 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 either 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 do not specifically identify the mechanism. For example, those offered Zinkid for sale by the NGO were no more likely to state "I purchased this because I trust you" than those in the for-profit treatment. We speculate that the results may still reflect a greater trust in the NGO when considering new products, but one that individuals do not self-identify as being a central reason for purchasing the product. The magnitude of this effect is large: take-up increases from 29% to 46%. 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). 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 depresses demand and an information effect whose direction depends on whether the potential learning is primarily positive or negative.

Table 4 presents the OLS results from estimating equation (4) where the outcomes of interest are measures of demand in Wave 2. 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 columns 1 and 3, those previously receiving the product for free are 11.8 percentage points (s.e.=3.6) and 12.4 percentage points (s.e.=6.0) 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 remains 5.9 percentage points (s.e.=5.5) lower than in the Sale treatment, but the difference is not statistically significant (column 5). The even-numbered columns display results for the quantity of units purchased. Again, the relative reduction of demand caused by prior free distribution is largest for Elyzole, followed by Panadol and then Zinkid. While the pattern of coefficients is consistent with the theoretical prediction that any negative demand effects from price anchoring could be opposed or even reversed by the potential for positive learning, we note that

none of the differences across products are statistically significant at conventional levels.

Finally, we do not find evidence that any anchoring effect of free distributions spills over to other health products. Columns 7 and 8 report 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 one other product offered by a different organization. As shown in the table, we cannot reject the null of no effect from prior free distribution of another health product in Wave 1. 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, spanning from a 7.8 percentage point reduction in the likelihood of purchase to a 15.4 percentage point increase. 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 Robustness and alternative explanations

The empirical results show that demand following a free distribution can be lower than following distribution at a market price. Thus far, we have posited that this can be the natural result of a tension between price anchors and learning. In this section, we first consider the qualitative evidence in support of this hypothesis 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. As described in Section 2.2.3, 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, and surveyors coded the responses into predetermined categories based on piloting of survey questions. As is shown in Figure 2, among those who decided not to purchase the offered good in Wave 2, 10.4% 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 the product for free. In contrast, only 2.2% of those in the Sale treatment responded similarly (p-value: 0.000). A further 4.1% of the Free treatment group stated that the product was too expensive versus 1.7% 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 seen in Wave 1 and there is little reason to expect differential survey effects across treatment groups.[36] 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 (see Section 2.2.4). Both speak against stock driving the results.

[36] See Section 2.1 for details on the experimental design and implementation.

Table 5 reports measures of stock on hand before the second marketing wave. 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 stock in Sale treatment of the Panadol group was actually larger than in the Free treatment.[37] 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 net of any stock effects 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 in Wave 1 on Wave 2 demand.

The second source of evidence against the stock mechanism is the post-marketing survey on the reasons respondents did not purchase products in Wave 2. As Figure 2 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 standard errors are large and the differences not

[37] Although those in the Sale treatment were 23 percentage points less likely to receive any Panadol, they could buy up to five units while free distribution was capped at one unit. Conditional on having received any Panadol, households in the sale group had on average 2.53 tablets left at the time of the stock check, compared to 1.03 tablets in the free group. The p-value on the two-sided t-test is 0.05. We adjust this measure to correct for higher take up in the free group and set the value of remaining tablets of all households who did not receive a product from us to zero. The unconditional average number of Panadol tablets remaining is 1.95 in the sale and 1.03 in the free group, the p-value on the two-sided t-test is 0.14.

statistically significant. Taken together, we consider this convincing evidence that stock is not driving the reduction in demand following a free distribution.

A second potential alternative mechanism is what we refer to as regime change story. Suppose that prior to our intervention people believed that Panadol was always sold and never given away for free.[38] 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 columns 5 and 6 in table 4). Thus, we rule out this "regime change" story.

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 bednets, where income effects could be quite large, 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

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

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 very low—about $0.80 per household. Moreover, villages were revisited an average of ten weeks later and this future visit was not announced at the time of the first. It seems implausible that people kept the funds they would have otherwise spent on drugs in the first wave of marketing 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 are positive externalities of the distributed drugs. The argument here would be that higher take-up in Wave 1 led to lower disease prevalence in communities in Wave 2 and hence lower utility from using the product in the second wave. 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. On the other hand, the deworming medicine Elyzole does have positive externalities. Dewormed children are less likely to transmit worms to their siblings and peers (Kremer and Miguel, 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 5% 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

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 profitable.

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 second wave 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

This study highlights an important tension between learning and price anchors. We design and implement a field experiment in Northern Uganda to explore this tension and find evidence of price anchoring consistent with models of reference-dependent preferences along the lines of Kőszegi and Rabin (2006). For products without scope for positive learning, subsequent demand is lower after a free distribution than after a distribution at market prices. We rule out plausible alternative mechanisms, most importantly stock, and report additional, qualitative evidence supporting reference dependence. By contrast, when the product has potential for positive learning, we do not find an effect of free distribution on subsequent demand. This result is in line with prior studies and consistent with a model in which prices affect subsequent demand both through reference-dependent preferences and by changing the share of the population that is directly informed about the product's value.

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 underpowered 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 it was offered by a for-profit entity or an NGO. However, we find that the identity of the distributor does matter for the sale of the lesser-known product, Zinkid. Individuals offered this product for sale by the NGO were nearly 50% more likely to purchase than those who were offered it by the for-profit. This finding should be interpreted with some caution, as this was not part of our intended tests in the design of the experiment. Furthermore, 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.

Finally, we note several considerations regarding external validity. 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 more attuned to any deviations from the norm.

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, 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 policy-makers aiming to increase social welfare. These considerations as well as a number of other parameters from which we abstract may influence the answer to the question of whether "to charge or not to charge?"

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Figure 1: Experimental Design

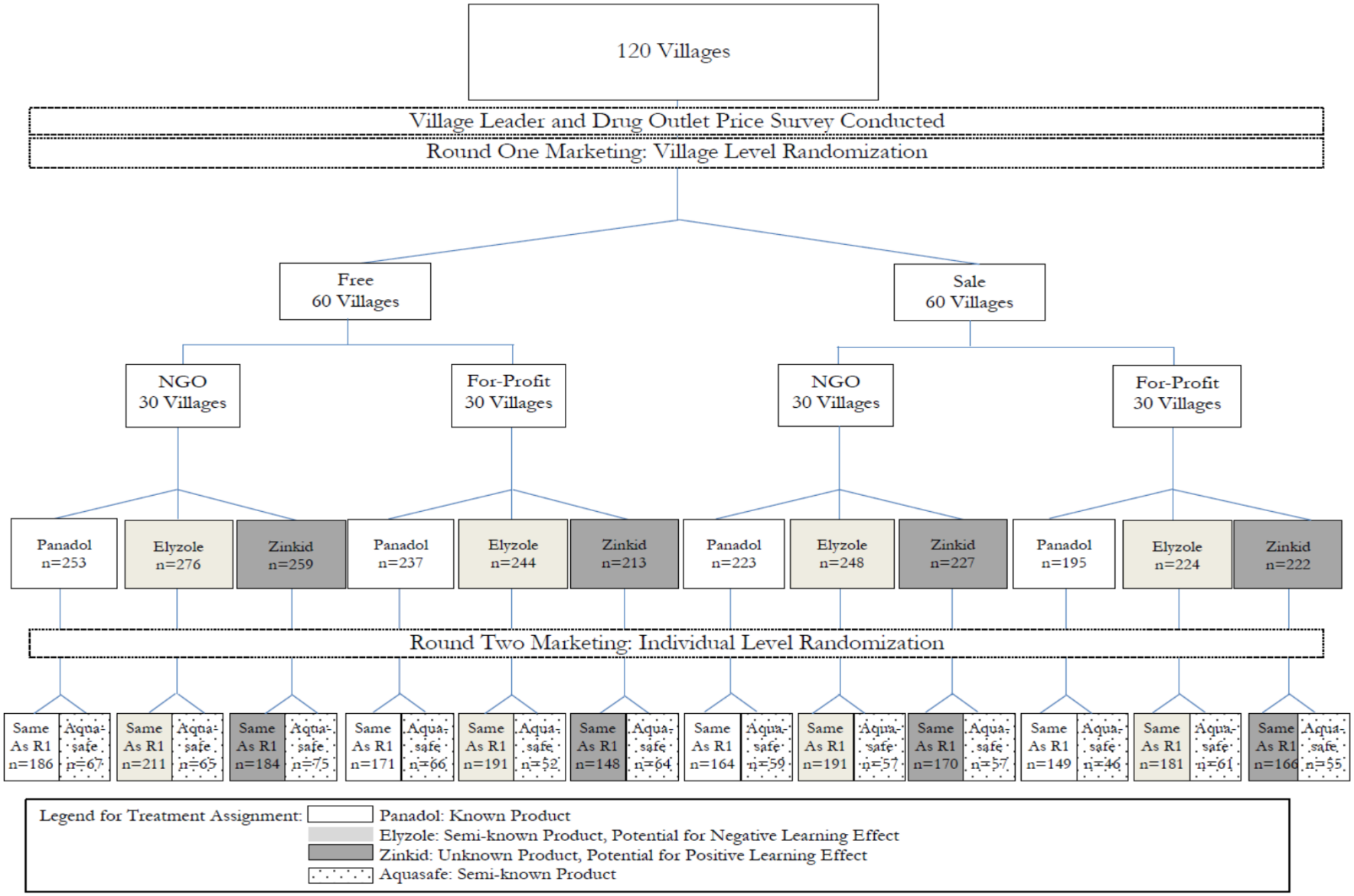

Figure 2: Reasons for Not Purchasing

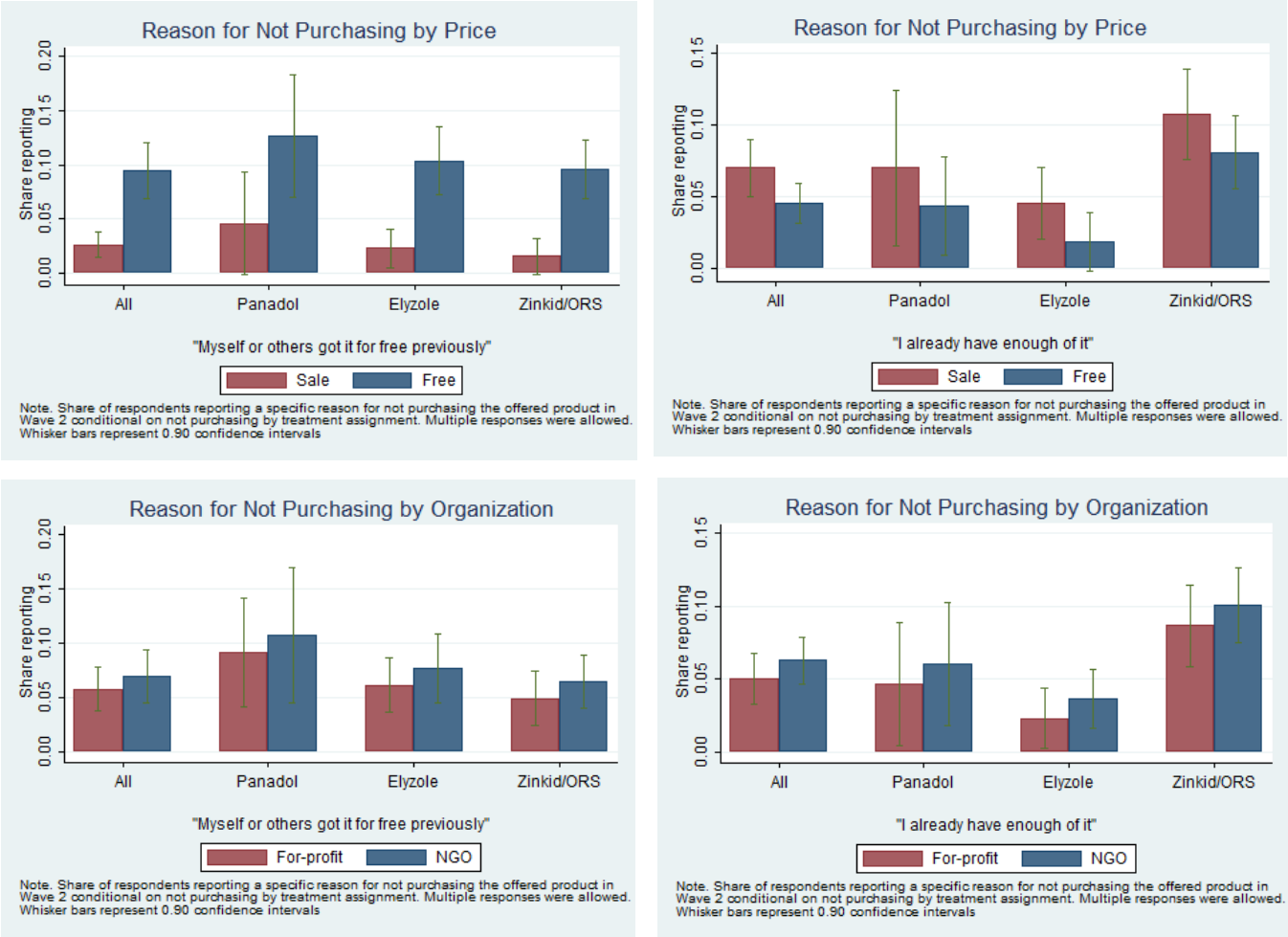

Table 1: Summary Statistics at the Individual Level & Village Level

	Wave 1 Treatment Assignment						
	Free (1)	Sale (2)	NGO (3)	For-Profit (4)	p-value of (1) vs (2) t-test (5)	p-value of (3) vs (4) t-test (6)	N of individuals or villages (7)
Individual Level							
Female	0.334	0.360	0.335	0.359	0.152	0.181	2887
	(0.012)	(0.013)	(0.012)	(0.013)			
Respondent Age*	43.355	42.979	43.607	42.686	0.723	0.383	777
	(0.698)	(0.795)	(0.683)	(0.813)			
Number of Children under 16*	4.523	4.383	4.456	4.470	0.423	0.934	779
	(0.117)	(0.128)	(0.117)	(0.129)			
Number of Cows Owned*	1.097	0.896	1.000	1.023	0.262	0.899	779
	(0.125)	(0.124)	(0.125)	(0.126)			
Village Level							
Number of Drug Outlets	1.167	1.367	1.167	1.367	0.483	0.483	120
	(0.187)	(0.214)	(0.196)	(0.206)			
Panadol Available	0.383	0.333	0.333	0.383	0.572	0.572	120
	(0.063)	(0.061)	(0.061)	(0.063)			
Elyzole Available	0.233	0.250	0.217	0.267	0.833	0.526	120
	(0.055)	(0.056)	(0.054)	(0.058)			
Zinkid Available	0.117	0.100	0.100	0.117	0.771	0.771	120
	(0.042)	(0.039)	(0.039)	(0.042)			
Free Distribution of Any Drug in the last 3months	0.500	0.483	0.433	0.550	0.857	0.204	120
	(0.065)	(0.065)	(0.065)	(0.065)			
Free Distribution of Deworming Drug in the Last 3 months	0.475	0.466	0.397	0.542	0.923	0.116	117
	(0.066)	(0.066)	(0.065)	(0.065)			
Free Distribution of Elyzole in the Last 3months	0.055	0.055	0.038	0.070	1.000	0.459	110
	(0.031)	(0.031)	(0.026)	(0.034)			
Attrition (individual level)							
Percent of Wave 1 Respondents Found in Wave 2	0.745	0.741	0.764	0.722	0.754	0.002	3884
	(0.010)	(0.010)	(0.010)	(0.010)			
Panel B: Outcomes (village level)							
Take-up in Wave 2 by Assigned Same Product Group	0.456	0.545	0.508	0.493	0.001	0.609	120
	(0.018)	(0.020)	(0.018)	(0.021)			
Take-up in Wave 2 by Assigned Different Product Group	0.541	0.552	0.546	0.548	0.813	0.964	120
	(0.030)	(0.035)	(0.032)	(0.034)			

Standard errors reported in parentheses. * indicates that a variable comes from accompanying methodology study. A product is "available" in a village if it is "mostly" or "always" available in at least one outlet/drugshop of the village.

Table 2: Summary Statistics of Respondents' Familiarity with Products

Drug	Percent reporting they recognize a shown drug	Percent of respondents who say they recognize the brand	Percent giving a price estimate (any brand)	Percent giving a price estimate (same brand)	n
Panadol	95	10	85	9	973
Elyzole	63	7	55	6	908
Zinkid/ORS	51	6	44	4	972
Zinkid (lower bound*)			16	1	972
Aquasafe	71	16	66	14	2019

These data were collected during the first wave by a marketer. Prior to marketing, we asked respondents about the two products that would not later be marketed to them. For the first column, the exact phrase we used is "Do you recognize this product that I have here? (Briefly describe what the product is, what it does)". For the second column, we asked, "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_____. The denominator is the number of respondents who were shown a given product. * 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 in Wave 1	Panadol		Elyzole		Zinkid	
Dependent Variables:	Take up	Quantity	Take up	Quantity	Take up	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)
NGO in Wave 1	0.010	-0.047	-0.022	-0.009	0.153***	0.184***
	(0.045)	(0.170)	(0.052)	(0.083)	(0.052)	(0.053)
Free in Wave 1	0.234***	-0.721***	0.435***	0.189***	0.686***	0.668***
	(0.029)	(0.119)	(0.036)	(0.051)	(0.034)	(0.033)
Free*NGO	-0.009	0.050	0.024	0.015	-0.156***	-0.188***
	(0.045)	(0.173)	(0.052)	(0.082)	(0.051)	(0.054)
Constant	0.779***	1.709***	0.503***	0.727***	0.292***	0.305***
	(0.049)	(0.188)	(0.060)	(0.086)	(0.066)	(0.062)
Control for Stratification Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	908	908	1,012	1,012	921	921
Adjusted R-squared	0.135	0.102	0.290	0.018	0.450	0.353
Test of equality of Free coefficient w.r.t. Panadol	N/A	N/A	0.000	0.000	0.000	0.000
Test of equality of Free coefficient w.r.t Elyzole	0.000	0.000	N/A	N/A	0.000	0.000
Test of equality of Free coefficient w.r.t. Zinkid	0.000	0.000	0.000	0.000	N/A	N/A
Mean of NGO*Sale	0.776	1.673	0.544	0.802	0.467	0.515
Mean of For-Profit*Free	1.000	1.000	1.000	1.000	1.000	1.000

The generic names for all three drugs are: *paracetamol* for Panadol, *albendazole* for Elyzole, *zinc* for Zinkid. 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. Village assignment to treaoups was stratified on the following four variables: (1) Categorical price data (three possible values: no data, above or at median price, or below median price), (2) Above or below the median of a seven-point remoteness index, (3) Above or below the median distance to health center. and (4) Whether there had been a recent distribution of drugs. To reduce the number of cells, stratification variables (1) to (2) and (3) to (4) were collapsed into a single dimension, respectively. 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 4: Demand in Wave 2

Product Offered in Wave 2	Panadol		Elyzole		Zinkid		Aquasafe	
Same As Wave 1?	Same		Same		Same		Different	
Dependent Variables:	Take up	Quantity	Take up	Quantity	Take up	Quantity	Take up	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NGO in Wave 1	0.034	-0.074	0.020	0.027	-0.014	0.009	0.041	0.023
	(0.041)	(0.166)	(0.058)	(0.098)	(0.053)	(0.061)	(0.061)	(0.093)
Free in Wave 1	-0.118***	-0.429***	-0.124**	-0.169*	-0.059	-0.067	0.038	0.076
	(0.036)	(0.155)	(0.060)	(0.094)	(0.055)	(0.058)	(0.059)	(0.111)
Free*NGO	0.045	0.372	0.004	-0.027	0.012	0.036	-0.082	-0.126
	(0.058)	(0.225)	(0.083)	(0.133)	(0.074)	(0.094)	(0.080)	(0.139)
Constant	0.946***	2.091***	0.498***	0.680***	0.238***	0.229**	0.548***	0.643***
	(0.066)	(0.221)	(0.083)	(0.137)	(0.086)	(0.090)	(0.082)	(0.133)
Observations	687	687	786	786	677	677	737	737
Adjusted R-squared	0.020	0.014	0.011	0.011	-0.002	-0.002	0.009	0.018
Test of equality of Free coefficient w.r.t. Panadol	N/A	N/A	0.929	0.131	0.296	0.017	0.003	0.001
Test of equality of Free coefficient w.r.t Elyzole	0.929	0.131	N/A	N/A	0.349	0.298	0.034	0.036
Test of equality of Free coefficient w.r.t. Zinkid	0.296	0.017	0.349	0.298	N/A	N/A	0.165	0.170
Mean of NGO*Sale	0.866	1.720	0.521	0.688	0.276	0.312	0.571	0.714
Mean of For-Profit*Free	0.709	1.363	0.379	0.495	0.233	0.240	0.566	0.762
p-value of Free + Free*NGO = 0	0.095	0.716	0.042	0.041	0.361	0.679	0.422	0.583

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. Village assignment to treatment groups was stratified on the following four variables: (1) Categorical price data (three possible values: no data, above or at median price, or below median price), (2) Above or below the median of a seven-point remoteness index, (3) Above or below the median distance to health center. and (4) Whether there had been a recent distribution of drugs. To reduce the number of cells, stratification variables (1) to (2) and (3) to (4) were collapsed into a single dimension, respectively. All regressions control for stratification variables. 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 5: Observed Usage Summary Statistics

Variable	Drugs	N Sale	N Free		n
Panel A: Number of respondents in usage checks					
Selected	All	177	183		360
Found	All	126	125		251
		Mean Sale (1)	Mean Free (2)	P-value (1)≠(2)	n
Panel B: Distribution & usage					
Respondents found for usage checks (percent)					
	All	0.71	0.68	0.72	251
Number of tablets distributed in Wave 1					
	Panadol	21.38	10.00	0.00	98
	Elyzole	8.76	6.00	0.00	84
	Zinkid & ORS	11.03	10.00	0.12	67
Proportion of tablets used					
	Panadol	0.90	0.90	0.88	98
	Elyzole	0.99	0.99	0.66	84
	Zinkid & ORS	0.53	0.51	0.90	67
Panel C: Remaining stock					
Mean tablets remaining, conditional on receiving any in Wave 1					
	Panadol	2.53	1.03	0.05	98
	Elyzole	0.16	0.04	0.43	84
	Zinkid & ORS	5.34	4.86	0.69	67
Mean tablets remaining, full sample					
	Panadol	1.95	1.02	0.14	98
	Elyzole	0.09	0.04	0.61	84
	Zinkid & ORS	2.08	4.85	0.00	67
Share of respondents who have positive stock, full sample					
	Panadol	0.28	0.18	0.18	98
	Elyzole	0.01	0.02	0.82	84
	Zinkid & ORS	0.23	0.60	0.00	67

The numbers in the table are based on product assignments rather than actual marketed products. In each village, three households who had received a health product in wave 1 were randomly selected for visual usage checks, which were conducted prior to wave 2. 'Number of tablets remaining, full sample' is the average number of tablets remaining per household, irrespective of whether or not they have received any of the product during our wave 1 distribution.

Table 6: 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 7: Heterogeneous Effects Model by 3-Month Prior Distribution

Product Offered in Wave 2	Panadol		Elyzole		Zinkid		Aquasafe	
Same As Wave 1?	Same		Same		Same		Different	
Dependent Variables:	Take up	Quantity	Take up	Quantity	Take up	Quantity	Take up	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NGO in Wave 1	0.023	-0.066	0.039	0.101	-0.017	-0.004	0.043	-0.003
	(0.049)	(0.180)	(0.081)	(0.127)	(0.060)	(0.072)	(0.068)	(0.112)
Free Distribution of Any Deworming Pill in the 3 Months	0.005	0.115	0.058	0.086	0.087	0.077	-0.008	-0.027
	(0.046)	(0.203)	(0.078)	(0.117)	(0.065)	(0.074)	(0.073)	(0.113)
NGO in Wave 1*Free Distribution of Any Deworming Pill in the 3 Months	0	-0.050	-0.014	-0.095	0.056	0.081	-0.052	-0.004
	(0.057)	(0.231)	(0.086)	(0.132)	(0.077)	(0.097)	(0.082)	(0.149)
Free in Wave 1	-0.096**	-0.418**	-0.093	-0.128	-0.015	-0.041	0.005	0.070
	(0.048)	(0.201)	(0.087)	(0.123)	(0.067)	(0.076)	(0.067)	(0.148)
Free in Wave 1*Free Distribution of Any Deworming Pill in the 3 Months	-0.061	-0.076	-0.050	-0.030	-0.078	-0.042	0.037	-0.027
	(0.056)	(0.238)	(0.089)	(0.135)	(0.077)	(0.095)	(0.084)	(0.151)
Free * NGO in Wave 1	0.060	0.412*	-0.010	-0.051	-0.016	0.003	-0.055	-0.099
	(0.058)	(0.239)	(0.088)	(0.134)	(0.075)	(0.093)	(0.079)	(0.139)
Constant	0.945***	2.039***	0.461***	0.620***	0.176**	0.173*	0.568***	0.668***
	(0.073)	(0.229)	(0.104)	(0.159)	(0.078)	(0.088)	(0.096)	(0.143)
Control for Stratification Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	669	669	764	764	657	657	723	723
Adjusted R-squared	0.018	0.011	0.008	0.007	0.003	0.003	0.005	0.014
Mean Free Distribution of Any Deworming Pill in past 3 Months	0.483	0.483	0.490	0.490	0.481	0.481	0.485	0.485

The generic names for all three 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. Village assignment to treaoups was stratified on the following four variables: (1) Categorical price data (three possible values: no data, above or at median price, or below median price), (2) Above or below the median of a seven-point remoteness index, (3) Above or below the median distance to health center. and (4) Whether there had been a recent distribution of drugs. To reduce the number of cells, stratification variables (1) to (2) and (3) to (4) were collapsed into a single dimension, respectively. 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 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):

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

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)

Product: deworming panadol ORS/Zinkid **Enumerator Name**:_____ **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 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 has been handed over.**

Step 1. 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) **[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 5---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

2) **[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: _____
_____

3) **[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

Step 2. [If the respondent purchased] Inform them that they have automatically been entered into a lottery. If they are chosen, they will be visited again in a few months by someone from our organization. If they can provide the exact packaging that they have purchased today (whether they have used the product or not) they will receive a prize.

Step 3. WOMEN ONLY – CONDOMS

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