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TO CHARGE OR NOT TO CHARGE:
EVIDENCE FROM A HEALTH PRODUCTS EXPERIMENT IN UGANDA

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ABSTRACT

In a field experiment in Uganda, we find that demand after a free distribution of three health products is lower than after a sale distribution. This contrasts with work on insecticide-treated bed nets, highlighting the importance of product characteristics in determining pricing policy. We put forward a model to illustrate the potential tension between two important factors, learning and anchoring, and then test this model with three products selected specifically for their variation in the scope for learning. We find the rank order of shifts in demand matches with the theoretical prediction, although the differences are not statistically significant.

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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, with particular relevance to the debate in the development aid community over the pricing of health products. These factors are also highly relevant for agriculture, where government policy often includes free or subsidized inputs and learning is a major issue. 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 help explain how current prices shape future demand.

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

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

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

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

demand during the low-price period. In addition to any direct benefit from this, those who purchase the product have an opportunity to learn directly about the product’s effectiveness. Depending on prices and individuals’ prior beliefs about the value of the product, this learning effect can either increase or decrease subsequent demand. On the other hand, lower current prices may serve as reference points or “anchors” that affect subsequent demand independently of intrinsic value.

We first develop a simple model of purchase decisions that combines the learning aspect of experience goods with reference-dependent preferences. The model makes several predictions about the effect of prices 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 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. 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 after our initial distribution, representatives from an unrelated, for-profit firm offered the households either the same or a new health product for sale at market prices. Our key outcome measure is households’ purchase decisions in this second distribution.

For health products in low-income countries, where free or heavily subsidized distribution is a common but controversial practice, the tension between learning and price anchors is particularly important. 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.

We find evidence supporting the presence of price anchors, consistent with mod-

els of reference-dependent preferences (Kőszegi and Rabin, 2006; Mazar et al., 2013; Heidhues and Kőszegi, 2014) where comparison effects dominate. Across all three products, demand in the second wave is lower following a free distribution than after a distribution at market prices. For the well-known product with little scope for learning, Panadol, demand in the subsequent sale is nearly 12 percentage points (14 percent) lower. We can rule out several alternative mechanisms for the difference, including the mechanical effect of having more of the product on hand if it had been previously distributed for free. Households’ qualitative responses also support our empirical conclusions: those who received free distribution are more likely to report that they do not want to purchase the product because they or someone in their community had received it for free in the past.

As predicted by the theory, the relative reduction in demand in percentage point terms 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. The pattern of effects is consistent with the theoretical prediction that any negative demand effects from price anchoring can be offset by positive learning; however, we note that none of the differences across products is statistically significant at conventional levels. This relative ranking across products is dependent on whether one analyzes the percentage point change or the percent change. A firm may be more interested in percents, which relate directly to elasticity and thus profit calculations. We focus on percentage point changes as this is typically the policy-relevant object. For example, measurement of the Millennium Development Goals focuses extensively on the proportion of populations covered by crucial health services (UNDP, 2009). It is also the norm in the experimental literature on health product pricing in developing countries (Cohen and Dupas, 2010; Ashraf et al., 2010; Dupas, 2014; Tarozzi et al., 2014).

These findings build on the results of Dupas (2014), which found that in the case of insecticide-treated bed nets (ITNs) in Kenya, a one-time subsidy had a positive impact on subsequent willingness to pay. Of the three products in our study, the closest comparable is Zinkid, which, like ITNs, has significant potential for positive learning. Like Dupas we put forward a parsimonious, latent-utility model for non-durable experience goods with the potential for reference-dependent utility. The three products in our study were specifically chosen to map to this

model by spanning a range of potential learning effects. They also have limited scope for income effects, helping us isolate the tension between learning and price anchors.⁴

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

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

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

We find overall negative effects on subsequent demand from prior free distribution, but 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. Nonetheless, while context and product characteristics may differ greatly and governments, firms and other organizations may have different objective func-

⁴The use of bed nets reduces the incidence of malaria and may thereby increase households' income and, in turn, future demand for additional bed nets (see footnote 27 of Dupas (2014) for more discussion). In our context, as discussed in Section 4, we do not believe any income effects would be substantial. We also would expect income effects to lead to increases in demand from free distribution, which is not what we find.

tions when distributing products, our results demonstrate that the tension between price anchors and learning is likely to be a critical factor in many cases.

2 Experimental design & data

2.1 Experimental design

Setting and sampling. We conducted our experiment in Gulu District in northern Uganda.⁵ We selected 120 villages for the study and from each of these villages randomly selected approximately 50 households from the household list kept by the village chief.⁶ Each village was divided geographically into three groups and each group assigned to a marketer.⁷

First wave of marketing. The first wave of marketing (Wave 1), conducted in October-November 2011, employed a two-level clustered randomization design, with randomization both at the village and individual level. First, villages were randomly assigned to one of four treatment groups in a two-by-two design.⁸ The

⁵We selected the Gulu District in order to conduct this study in conjunction with a methodological study that compared the accuracy of data collected by professional surveyors hired and trained by Innovations for Poverty Action to data collected by “community knowledge workers” (CKWs), local community members hired by Grameen Foundation to both disseminate and collect information. The Gulu District was destabilized by an insurgency from 1987 until 2006. In the wake of the insurgency, the area received a large amount of NGO and government attention. Many NGOs were active in reconstruction and service provision, including providing free health care and health products. Relative to other regions in Uganda, the Gulu District is likely at the upper end of the distribution in terms of prior exposure to free or heavily-subsidized distributions of health goods. We believe this represents a conservative test for the effect of past prices on current demand based on our expectation that prior exposure to free distributions would mute the effect of any single subsequent distribution; however, demand could be particularly sensitive in an environment with high NGO activity.

⁶Of these 120 villages, 72 were participating in the contemporaneous methodological study. These villages were selected based on their availability of certain administrative data. The remaining 48 villages were selected randomly from an administrative government list of villages in Gulu. The number of households drawn in each village depended on the number of respondents from the parallel study, which in turn was determined by the number of households for which institutional data were available. The sample of the parallel study consisted of names of recipients for NGO and government services, including free bed nets, free seedlings, and tarpaulins, as well as clients of a local bank. All 859 such individuals were included in the sample, and the remaining households were randomly selected from household lists maintained by local village leaders in order to arrive at a sample of approximately 50 households per village. In Uganda, the village chief is referred to as Local Council 1 Chairperson (“LC1”).

⁷Grouping was done based on logistical ease. Groups were not always of equal size, but rather defined so as to minimize distances between respondents for each marketer.

⁸Village assignment to treatment was block randomized according to two variables. The first, price environment, included information about pricing and drug availability with three possible categories: (1) no drug outlets or none of our drugs; (2) no prices above the median or distributed

first treatment dimension was the price of the product, either free (“Free”) or sold (“Sale”). The second dimension was the type of distributing organization: either a not-for-profit, non-governmental organization (“NGO”) or a for-profit business (“For-Profit”). Thirty villages were assigned to each of the four treatment cells. Table 1 illustrates balance across our village treatment assignments.

Then, at the household level, we randomly assigned one of three products to be offered to each household: Panadol (paracetamol, a painkiller), Elyzole (albendazole, a deworming medication), and a combination pack of Restors and Zinkid (oral rehydration salts, “ORS” and zinc supplements, the World Health Organization’s recommended treatment for childhood diarrhea). For the Sale treatment group, we used the same price for the entire study. We set the price for the Sale group to be slightly above the average perceived price (from a price perception survey, see below) in order to minimize the chance that respondents were purchasing only in order to resell and to approximate a market price (i.e., the perceived price plus a small add-on for the convenience of buying at one’s home).⁹

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

for free; and (3) at least one price above the median. The second, remoteness, also had three categories: (1) easy to travel and close to health center; (2) difficult travel or far from health center; and (3) difficult travel and far from health center.

⁹In earlier circulated versions of this paper, we referred to this as selling above the market price, but we have changed the language to refer to it as perceived price for two reasons. First, because there are no posted prices, most individuals’ set their final prices through a process of bargaining. Fitzpatrick (2014) finds that 48 percent of customers at informal drug shops successful bargain over the price of anti-malarial medicines. Second, though our prices may have been slightly higher than the average perceived price, our door-to-door distribution also builds in transport and convenience, which we would expect to influence households’ perception of how competitive our prices are relative to other alternatives. The prices set in the first wave were as follows: Panadol: UGX 500 (\$0.20) for a strip of ten tablets, Elyzole: UGX 1,800 (\$0.71) for a pack of six tablets, Restors/Zinkid combination pack: UGX 2,000 (\$0.79) for one sachet of Restors and ten tablets of Zinkid.

ID-cards from the relevant partner organization. The field marketers were all locally recruited, reducing communication barriers.

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

Marketers delivered product- and entity-specific sales pitches and answered questions about the product. A pharmacist trained the marketers on how to explain usage and dosage guidelines.¹⁰ See Appendix B.1 and B.2 for details on the marketing scripts.

In Wave 1, we offered one unit of the assigned product to households in the Free treatment arm and five units to those in the Sale treatment.¹¹ Prices were non-negotiable. Once this transaction had been completed, marketers administered a questionnaire to respondents in the Sale treatment group about why they decided to buy or not to buy and who might use the product.¹² In all cases, marketers had only one day to reach all respondents in each village. Marketing was not continued on a second day in order to reduce the possibility of spillovers of information or expectations across respondents.

Out of the original 5,708 households identified to be in the study, 3,884 were found in this first wave of marketing. Although this is a higher level of attrition than often found in studies in developing countries, it was a deliberate methodological decision to adhere to a more natural marketing process. We wanted to avoid marketing procedures that deviated considerably from normal operating practices of NGOs or firms, so that the observed reactions of respondents would also be more natural. In particular, we expected that returning on several consecutive days to a remote village to search for a specific respondent by name would be perceived as

¹⁰Marketers gave respondents information on dosage, storage and recommended use of the respective product both verbally and in writing in Acholi, the local language. This information was based on the instruction sheet of the drug and formulated in consultation with a pharmacist and board member of the Ugandan National Drug Authority.

¹¹One unit corresponds to the smallest amount of each product that could be sold separately. For Panadol this was 10 tablets, for Elyzole this was 6 tablets, for Restors/Zinkid this was 1 sachet of Restors and 10 tablets of Zinkid, and for Aquasafe this was 8 tablets. Prices are given above. Only 2.5 percent of households in the Sale treatment purchased five units, suggesting that the cap on the quantity of units for sale was only rarely, if ever, binding.

¹²This survey was not conducted in the Free group in order to keep the interaction more natural.

atypical behavior for an ostensibly profit-maximizing firm. In each attempt to locate specific respondents we found approximately 75 percent of targeted individuals.

The three products were chosen deliberately to capture a range of potential learning effects that could influence purchase decisions. Panadol is a common pain reliever and was by far the most well-known product. Most respondents were likely to have been familiar with the product (95 percent) although only few with the brand itself (10 percent). The generic version of Panadol is widely available in most drug shops, and we expect little scope for learning. Elyzole was less well-known as a brand, but other brands of deworming medication with the same active ingredient (albendazole) have been widely distributed. Based on the relative salience of immediate side-effects, we expected that any learning effects would be negative despite potential for long-run benefits (Miguel and Kremer, 2004). Zinkid was sold in combination with Restors, an oral-rehydration salt, following clinical recommendations (World Health Organization, 2005). While Restors was a new brand,¹³ the generic version (ORS) was widely used, recognized and freely available from health centers.¹⁴ However, the importance of zinc supplements in combating diarrhea had only recently been established in the global health literature.¹⁵ As such, Zinkid represents a new brand and product for which we expect there to be scope for positive learning. In a study carried out with Zinkid users by our partner the Ugandan Health Marketing Group in 2012, 93 percent of zinc users believed that the product was an effective treatment for diarrhea, citing a quick end to diarrhea and fast recovery by the child as primary reasons for this belief.¹⁶ Table 2 presents descriptive

¹³Restors is an ORS formulation with lower osmolarity which was recommended by the WHO in 2006 (WHO 2006). The lower osmolarity results in lower stool output by children with diarrhea, as compared to the old formulation Hahn et al. (2002).

¹⁴One concern about bundling ORS and zinc is that children and caregivers often cite the bad taste of ORS as a reason for not using it (Freedman et al., 2010). However, ORS is a widely known therapy recommended by the WHO since 1980 (da Cunha and Cash, 1989). If any learning occurs with ORS in our sample it occurs because the formulation we distributed had lower osmolarity and therefore may have had a slightly improved taste and because the low osmolarity formulation results in reduced stool output.

¹⁵Zinc became part of the WHO guidelines for the treatment of diarrhea in 2006. Larson et al. (2009) find that use of zinc supplements in rural areas lags adoption among urban and high income individuals. Evidence from studies in Tanzania and Benin suggest that while the prescription of zinc for childhood diarrhea is increasing, the majority of diarrhea cases are not yet treated with zinc (Sanders et al., 2013).

¹⁶The three products also differ in terms of who would be the target user, which could affect the scope for learning. The type of Panadol used was aimed at adults only; children under 12 were not allowed to use it. Although Elyzole could be used by people of any age (except babies), parasitic infestations are most acute amongst children. Zinkid was a product specifically aimed at children, with a target age group of six months to five years.

results from the price perception and product awareness survey.

Second wave of marketing. We conducted the second wave of marketing (Wave 2) on average ten weeks after Wave 1, in December of 2011.¹⁷ The sole purpose of Wave 2 was to get an outcome measure of respondents’ willingness to pay for health goods. In order to avoid reputation effects from the first stage, we partnered with a different for-profit firm, Surgipharm Uganda Ltd (“Surgipharm”). Again, marketers were employed by the partner, but recruited, trained and monitored by the study team. In order to reduce association between the two waves, we changed the wording of all scripts without significantly affecting the content. In order to reduce the probability that respondents associated Wave 2 with Wave 1, we also assigned marketers to villages such that individual marketers did not visit the same village twice. While there may be time trends in the demand for health products, we do not believe there is any reason to expect seasonal fluctuations in demand to vary according to treatment status.¹⁸

As a further test of the scope of price anchoring effects, we investigate whether having received any product for free affects demand for other health products. We therefore assigned 25 percent of households to be offered a fourth product not offered in Wave 1, Aquasafe, a product designed for home water purification. The concept of water purification was well-known and understood; however, although Aquasafe is one of the two leading brands for water purification, the name itself was not well known by respondents (only 16 percent recognized the brand, as shown in Table 2). Since no learning about specific product characteristics takes place across products, the cross-product test allows us to assess whether price anchoring will occur for broadly construed product categories, such as “health products”.¹⁹ In the second

¹⁷The minimum number of weeks between marketing waves was 6, the maximum 12 weeks, and the median is 10 weeks. Timing varied for logistical reasons, such as weather and holidays. We do not find any evidence that observed effects are correlated with differences in the number of days between waves.

¹⁸Panadol is a pain-killer that is used frequently to treat a variety of illnesses year-round, especially as it often means avoiding a visit to the health center. The Ugandan Ministry of Health suggests preventative deworming of children every three to six months, so we would expect participants to demand more deworming medication at the time of our second visit (Ministry of Health, Republic of Uganda, 2012). Childhood diarrhea is more common during the rainy season (Ahmed et al., 2008), therefore we might expect higher demand for Zinkid to treat diarrhea in Wave 1 when rains were more common.

¹⁹The 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).

marketing wave, the only randomization was the household-level assignment of the product: 25 percent of households were marketed the new product, Aquasafe, and 75 percent the same product from Wave 1. Figure A1 summarizes the experimental design.

2.2 Data

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

Price perception survey. Immediately prior to offering the product, marketers administered a price perception survey to 50 percent of respondents in Wave 1. After introducing themselves, marketers showed respondents the two products *other than the one assigned to that individual* to avoid potential anchoring effects on the product about to be offered for sale or gift. After a brief description of the use of the product in general, respondents were asked about their familiarity with the product and brand. If they were familiar with the product, they were asked where they could purchase it and what price they would expect to pay. In Wave 1, we solicited price perceptions of the three goods distributed in the wave. In Wave 2, individuals were asked only about the new product, Aquasafe.

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

Observational usage data from physical observation of packaging. During Wave 1, all respondents who had received a product, whether for free or pur-

chased, were informed that that they had also been entered into a lottery. If selected, they would need to present the product packaging (blister packs) in order to claim their prize. It was clearly stated that the prize did not depend on how much of the product was used, only on whether they presented the blister packs. Six to eight weeks after Wave 1 (two to four weeks before Wave 2), surveyors made unannounced visits to a sample of 329 households that received a product in Wave 1 and recorded how many tablets were remaining in the blister packs.²⁰

3 Theoretical framework

We put forward a model of households' decisions to purchase non-durable health products that includes both price anchoring and learning. With our focus on these elements, we abstract away from other potentially important issues, such as health externalities, learning from one's neighbors, expectations about product quality, knowledge of price distribution, risk aversion, and habit formation. While the mechanisms we describe are applicable to repeated purchase opportunities, the key features can be seen in a simple two-period, latent utility model. This set-up differs from typical settings in which experience goods are analyzed in that (1) rather than constrain the distributor to be a profit maximizer, we remain agnostic regarding its objective function and (2) similar to Dupas (2014), we enrich the latent utility framework to allow for gain-loss utility. Where required, additional derivations and proofs appear in Appendix A.

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

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

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

²⁰Surveyors were given details about how many units of the product each respondent had received, and so were able to verify whether all packaging was present. Furthermore, all blister packs distributed by marketers in Wave 1 had been discretely marked so that they could be identified as packaging distributed by our marketers, rather than the same product obtained from elsewhere.

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

Households are heterogeneous and differ in their true value of the product, v_i , where $v_i = \bar{v} + \sigma_{iv}$. For analytical tractability, we assume that this true value is normally distributed, $v_i \sim N(\bar{v}, \sigma_v^2)$. In period 0, a share of the households, $\alpha_0 \in [0, 1]$, is informed of their true values. The remaining households receive a signal of their value, $\tilde{v}_{it} = \bar{v} + b_{it}$, where $b_{it} \sim N(b, \sigma_b^2)$ and b captures the mean bias in the population.²¹ Note that we are explicitly allowing for the possibility that the expected value of the product in the uninformed population may differ from the truth. If households tend to be optimistic about the value of a product, b will be positive; for pessimistic beliefs, b will be negative. For informed households, $v_{it} = v_i$, i.e., the true value. 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.

²¹This is an alternative representation for the definition of pessimistic and optimistic customers used by Shapiro (1983).

The share of individuals purchasing in period t can be expressed as follows:²²

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

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

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

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:

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

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 $\sigma_U^2 > \sigma_I^2$.²³

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:

²²Note that this model implicitly assumes that individuals cannot store the product. They do not buy today with the intent of consuming in a subsequent period. This assumption is important. If individuals could store the product for later consumption, individuals who received the product for free in round 1 may carry over stock into round 2, mechanically reducing demand. In Section 4.3 we discuss the empirical support for the assumption and show that individuals in our experiment indeed do not appear to be storing the product for future consumption. We also assume, consistent with the work of Shapiro (1983), Milgrom and Roberts (1986), Tirole (1988) and Villas-Boas (2004), that consumers do not have an experimentation motive for purchases. Such experimentation is analyzed in Bergemann and Välimäki (1996, 2006) and would not substantively alter the predictions of this theoretical framework.

²³While 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.

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

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 hypothesis regarding the presence of gain-loss utility (price anchors) that we can test with the distribution of Panadol, a well-known product for which we can reasonably assume that everyone knows the value.

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

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

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

It will be useful to define the concept of *scope for learning* by which we mean that (i) at a particular future price the expected demand for a currently informed

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

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

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

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

Taken together, this leads to two additional predictions.

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

When there is scope for positive learning, an increase in the share of uninformed individuals (a decrease in α_1) will further increase the scope for positive learning. If uninformed individuals are generally pessimistic about a product's true value and

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

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

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

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

4 Results

In our setting, free health goods can affect demand through two different mechanisms: price anchoring and learning. We generated exogenous variation along three dimensions: whether a product was offered for free or for sale in Wave 1, whether it was offered by an NGO or a for-profit company in Wave 1, and the product a

household was offered. The product price and the type of distributing organization were randomly assigned at the village level, while the product type was assigned at the household level. To estimate our treatment effects, we run the basic specification

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

where y is a measure of demand (either a binary indicator of take-up or the total quantity purchased/received), i represents households, j represents villages, and t represents time (Wave 1 or Wave 2). NGO is a dummy variable that takes the value 1 if a household was approached by a representative of an NGO in Wave 1 and 0 if approached by a for-profit. The dummy variable $Free$ takes the value 1 if a household was offered the product for free in Wave 1 and 0 otherwise. Coefficients of interest are the betas. β_1 captures the effect of an NGO being the distributing organization in Wave 1, β_2 the effect of being offered a product for free in Wave 1, and β_3 the effect of the interaction, i.e., being offered a free product by an NGO in Wave 1. X_{ij} is the vector cross product of the two stratification variables: a price index and a remoteness index. ε_{ijt} represents the idiosyncratic error, which we cluster at the village, the level of randomization.²⁴ We estimate equation (4) for the pooled sample and for each product individually.

4.1 Take-up in Wave 1

Table 3 shows the results, by product, from estimating equation (4) for Wave 1. The odd numbered columns show the effects of treatment assignment on take up defined as a binary variable equal to 1 if a household purchased or accepted any quantity of the offered product and 0 otherwise. The even numbered columns report the quantity effects as measured in units of the product.²⁵

Unsurprisingly, take up was much higher among those who were offered health products for free compared to those offered them for sale. As the odd-numbered columns show, among households in the for-profit group, being offered the product for free increased binary take up by 43.5 percentage points for Elyzole, 23.4 per-

²⁴Stratification was primarily done to ensure balance. Although power is limited for subsample analyses, we do examine whether results are heterogeneous regarding remoteness and price levels. The results do not exhibit any significant heterogeneity along these dimensions.

²⁵The 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.

centage points for Panadol, and 68.6 percentage points for Zinkid. All coefficients are statistically significant with p-values below 0.01.²⁶

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 percent) higher than for those in the Free treatment. As described above, households in the Sale treatment could purchase up to five units of the assigned product while distribution in the Free treatment was limited to one unit per household. In the case of Panadol, this leads to a reversal in the sign of the treatment effect between the binary and quantity regressions. While not all of the households in the Sale treatment purchased the product, those who did so purchased more than one unit on average.

Table 3 also shows that in the case of the unknown product (Zinkid), households were substantially more likely to purchase the product when it was offered for sale by a NGO rather than a for-profit entity. This difference is both statistically and economically significant: a 15.3 percentage point increase in take up and a 60.3 percent increase in total quantity purchased. Recall that the marketing scripts differed only in their description of the seller’s identity and motives. All information presented about the product itself was identical across the four treatment arms. Differences in the take-up rate could result 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 suggest a potential mechanism. Those offered Zinkid for sale by the NGO were more likely than those in the for-profit treatment to cite the product’s health benefits as a reason for purchase (p-value: 0.059); however, they were no more likely to state “I purchased this because I trust you.” We speculate that the results may still reflect a greater trust in the NGO when considering new products, but individuals are not explicitly aware of the NGO’s role in forming their impressions. The magnitude of this effect is large: take-

²⁶The 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.

up increases from 29 percent to 46 percent. This is consistent with other emerging work that points to the potential role of non-profit organizations as trust builders and may have important policy implications for organizations seeking to encourage the adoption of new technologies (Cole et al., 2013; Karlan, 2014). While our study design does not allow us to speak further to the mechanisms behind this effect, we believe future research into the role played by NGOs in stimulating demand for new products would be valuable.

4.2 Demand in Wave 2

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

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

For each of the three products offered in Wave 1, subsequent demand is lower in Wave 2 if the product was initially offered for free. For Panadol and Elyzole, the results are substantial and statistically significant. As shown in columns Panel A, columns 2 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 4). Panel B displays 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.

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

Finally, we do not find evidence that the anchoring effect of free distributions spills over to other health products. Column 4 reports the effect of Wave 1 treatment status on the Wave 2 purchase decisions for a new product, Aquasafe. Note that because there is no reason to suspect cross-product learning, this is a test of whether free distribution of one health product moves the reference point for another. Naturally, this is not dispositive. We are testing potential cross-product spillovers from one of three particular products to another product offered by a different organization. We cannot reject the null of no effect. While the 95%-confidence interval rules out a cross-product effect as large as the own effect of free distribution for Panadol or Elyzole, it remains quite large with a 95%-confidence interval from -7.8 to +15.4 percentage points. We also do not see statistically significant differences between prior distribution by an NGO and prior distribution by a for-profit, though our estimates are imprecise.

4.3 Discussion and alternative explanations

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

Qualitative evidence from the post-marketing questionnaire supports the role of price anchors in reducing relative demand following a free distribution. After the Wave 2 distribution, the marketers asked all respondents why they made their purchase decisions. The question was asked in an open-ended way, and surveyors coded the responses into predetermined categories based on piloting of survey questions. As is shown in Figure 1, among those who decided not to purchase the

offered good in Wave 2, 10.4 percent of respondents in the Free treatment stated that they did not purchase the product because either they or others whom they knew had previously been given it for free. In contrast, only 2.2 percent of those in the Sale treatment responded similarly (p-value: 0.000). A further 4.1 percent of the Free treatment group stated that the product was too expensive versus 1.7 percent in the Sale group (p-value: 0.027). While these responses are subject to all the usual qualifications regarding self-reported explanations for behavior, the Wave 2 distributors were affiliated with a different entity than either of those seen in Wave 1, ameliorating concerns over experimenter demand effects. Furthermore, there is little reason to expect differential survey effects across treatment groups. Taken at face value, these responses would explain the entire difference in Wave 2 purchase behavior between the Free and Sale treatments.

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

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

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

In the case of Zinkid, those in the Free treatment did have more tablets remaining. To the extent that stock affects demand, this should lower relative demand for

those in the Free treatment. In contrast to the other two products, this suggests that our estimates would be an upper bound on the magnitude of the effect. However, Zinkid, the product for which we expected some scope for positive learning, is the product for which we do not find a statistically significant negative effect of free distribution on Wave 2 demand.

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

A second potential alternative mechanism is a regime change story. Suppose that prior to our intervention people believed that Panadol was always sold and never given away for free.²⁷ Suppose further that there was significant uncertainty about the pricing regime for Zinkid. Since it is a largely unknown product, people could believe it may or may not be given away for free. If the individuals who received Panadol for free in Wave 1 believed that this indicated a regime change—that Panadol would now be distributed occasionally for free—this may have had a larger effect on their price reference point than for Zinkid. While we consider this a plausible mechanism following free distribution by an NGO, we do not find it credible in the case of for-profit distribution. There is no reason to think that for-profits would shift to a give-it-away-for-free-always regime. Yet, we do not find a difference in treatment effects between the NGO and the for-profit group for Zinkid (see column 4 in Table 4). Thus, we rule out regime change.

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

²⁷Indeed, according to our village leader survey, only in 1 out of 120 villages had Panadol ever been distributed door-to-door for free.

effects of the products in this study to be relatively modest.

Fourth, liquidity may have affected demand. Since households who received the product for free effectively received a transfer, they may have had more money available when marketers appeared in Wave 2. However, any effect along this dimension would tend to increase demand in the Free treatment. We would also expect any effects to be quite small. The magnitude of the transfer was low—about \$0.80 per household. Moreover, villages were revisited approximately ten weeks later and this future visit was not announced at the time of the first. It seems implausible that people kept the funds they would have otherwise spent on drugs in Wave 1 for a full ten weeks. Finally, to mitigate liquidity constraints, flyers were distributed a few days prior to each marketing visit to allow respondents to get money ready.

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

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

Seventh, higher prices may signal higher quality (Milgrom and Roberts, 1986; Heffetz and Shayo, 2009; Ashraf et al., 2013). All else equal, being offered a product for a higher price should then increase later demand just as we would expect from the price anchoring model. However, the signaling mechanism should have a

larger effect for products with more uncertainty about the benefits and would have the exact opposite effect of our model of experience learning, i.e., positive prices should increase relative demand for the least well-known products. While our point estimates across products are in line with the anchoring mechanism rather than the quality signal alternative, we again note that the differences in these estimates are not statistically significant. We cannot rule out the possibility that prices as a signal of quality may explain some of the differences in demand following free and sale distributions. Since these mechanisms have distinct policy implications, we think further research to distinguish their effects would be useful.

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

5 Conclusion

We examine the pricing policy tradeoff between learning and price anchors. To do this, we design and implement a field experiment in northern Uganda and find evidence of exactly such a tradeoff. Consistent with models of reference-dependent preferences (Kőszegi and Rabin, 2006; Mazar et al., 2013; Heidhues and Kőszegi, 2014), free distribution lowers subsequent demand.

To study the tradeoff between learning and price anchors, we then examine individually three products specifically chosen to span a range of potential learning effects. For the two products without potential for positive learning (Panadol & Elyzole, for pain relief and deworming, respectively), we find that subsequent demand is lower after a free distribution than after a sales distribution. For Zinkid, which we argue has potential for positive learning, we do not find such an effect.

Positive learning appears to offset the price anchoring effect. However, although each of the above stated results are statistically significant, the differences across the products are not. We note that our model correctly predicts the ordering of the demand effects when computed in percentage point terms, the standard unit of measurement in this literature, which focuses on coverage rates for their policy relevance. We rule out plausible alternative mechanisms, most importantly stock, and report additional, qualitative evidence supporting reference dependence as the mechanism behind lower demand.

Our results help reconcile empirical findings from marketing and psychology demonstrating a large role for price anchors with those from recent field experiments in the context of health goods in low-income countries, which find no evidence that prices have meaningful non-budget-constraint effects. While lower prices today can dampen future demand by setting low price reference points, opportunities to positively update one’s beliefs about a product’s value may blunt this effect. We also examine whether price anchors for one product spill over to the demand for another. While we do not find evidence of such spillovers, we also note that this test is 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 the product 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 14 percentage points (nearly 50 percent) more likely to purchase than those who were offered it by the for-profit. The effect does not persist to the subsequent distribution by a third-party, for-profit; however, the immediate observed effect is economically large and further research along this dimension could provide welcome insight into how to most effectively introduce new products, particularly in low-income countries (Cole et al., 2013; Karlan, 2014).

We contribute to three distinct strands of research. First, we provide additional evidence for the importance of price anchors in an important, non-laboratory domain of economic behavior. Second, we build on Dupas (2014) to contribute to the literature on experience goods pricing (Nelson, 1970; Villas-Boas, 2004; Shapiro, 1983; Bergemann and Välimäki, 2006) by highlighting the essential tension between learn-

ing and the potential for prices to directly affect potential consumers’ willingness to pay. Our study design highlights the insight that the impact of free distribution on later demand depends critically on whether users have a positive or negative experience with the product. This mechanism may be particularly important in the case of pharmaceutical demand (Crawford and Shum, 2005) but is also applicable to agricultural products and other goods where subsidies or discounts are common policy instruments.

Third, we directly inform the often controversial debate on subsidized distribution of health products, particularly in low-income countries. The motivations for free or subsidized distribution are numerous: to account for positive externalities (Miguel and Kremer, 2004), to provide people an opportunity to learn about the value of the good (Dupas, 2014), to account for behavioral biases that lead to sub-optimal 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).

Finally, we note several considerations regarding generalizability. The experimental setting of northern Uganda has a large NGO presence and a history of free distribution. In principle, this could either dampen the effect—because our marketing campaign is a small part of individuals’ experience with free distributions—or amplify it if individuals have become accustomed to the activities of NGOs and thus more attuned to any deviations from norms regarding which specific products get subsidized.

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

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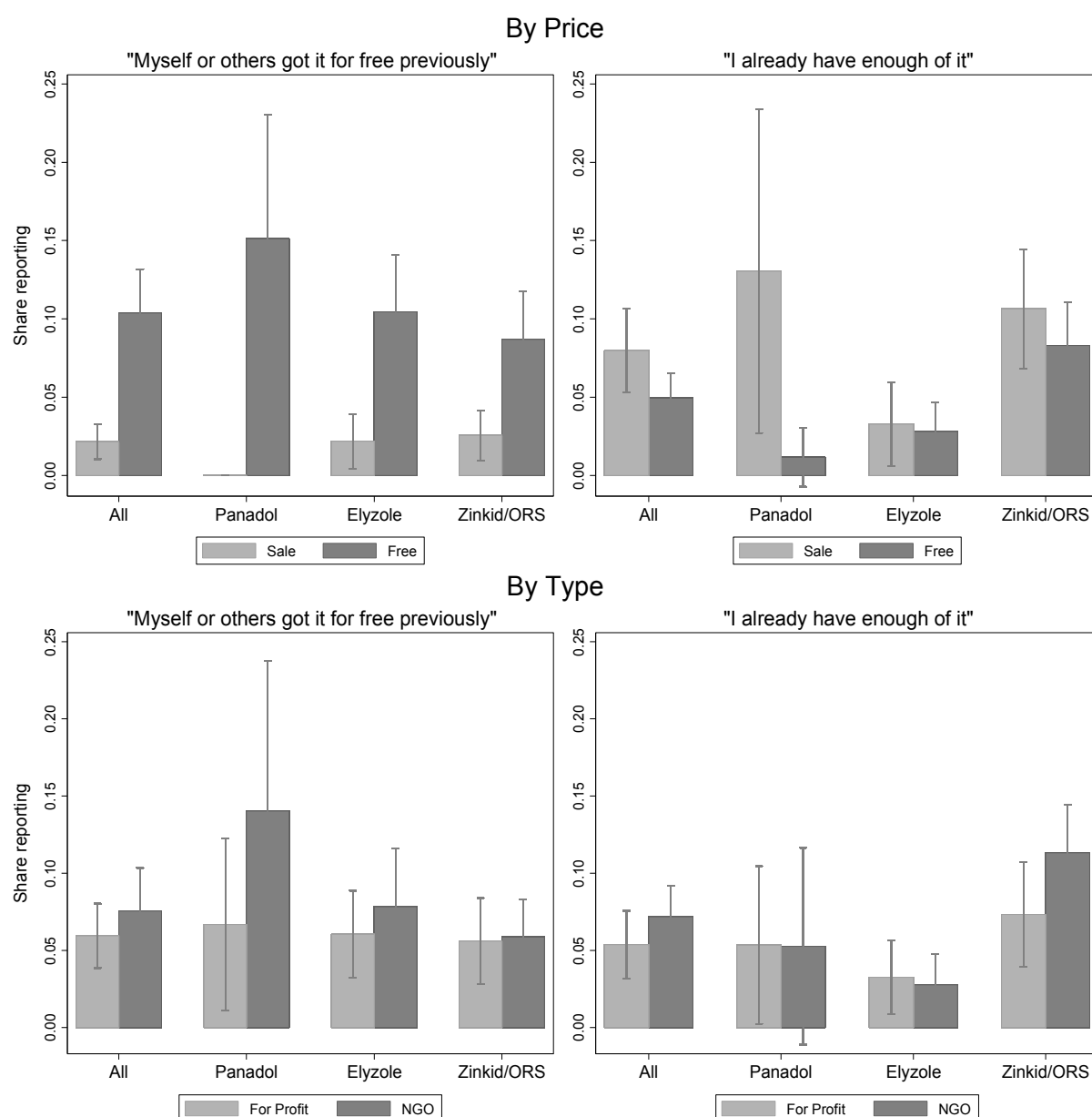
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Figure 1: Reasons for Not Purchasing, Wave 2



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

Table 1: Baseline Summary Statistics
Means & Standard Deviations

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

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

Table 2: Summary Statistics of Respondents' Familiarity with Products

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

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

Table 3: Demand in Wave 1

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

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

Table 4: Demand in Wave 2

Product Offered in Wave 2 Same As Wave 1?	Pooled Same (1)	Panadol ^a Same (2)	Elyzole ^a Same (3)	Zinkid ^a Same (4)	Aquasafe ^a Different (5)
Panel A: Take-up					
NGO in Wave 1	0.017 (0.032)	0.033 (0.040)	0.027 (0.056)	-0.002 (0.051)	0.054 (0.059)
Free in Wave 1	-0.100*** (0.036)	-0.116*** (0.036)	-0.118* (0.061)	-0.052 (0.054)	0.044 (0.060)
Free*NGO	0.017 (0.051)	0.051 (0.058)	-0.004 (0.086)	-0.002 (0.074)	-0.106 (0.078)
Constant	N/A ^c	0.862*** (0.054)	0.388*** (0.062)	0.234*** (0.065)	0.457*** (0.066)
Observations	2150	687	786	677	737
Test of equality of Free coefficient w.r.t.					
Panadol	0.094	N/A	0.980	0.228	0.003
Elyzole	0.208	0.980	N/A	0.325	0.037
Zinkid	0.798	0.228	0.325	N/A	0.176
Mean of NGO*Sale	0.555	0.866	0.521	0.276	0.571
Mean of For-Profit*Free	0.480	0.709	0.379	0.233	0.566
p-value of Free = 0	0.007	0.001	0.057	0.330	0.463
p-value of Free + Free*NGO = 0	0.017	0.131	0.038	0.295	0.216
Panel B: Quantity^b					
NGO in Wave 1	-0.004 (0.069)	-0.086 (0.172)	0.048 (0.096)	0.022 (0.059)	0.052 (0.092)
Free in Wave 1	-0.214*** (0.073)	-0.429*** (0.151)	-0.154 (0.097)	-0.060 (0.057)	0.101 (0.111)
Free*NGO	0.110 (0.114)	0.376 (0.237)	-0.056 (0.138)	0.021 (0.095)	-0.176 (0.142)
Constant	N/A ^c	1.813*** (0.181)	0.510*** (0.108)	0.216*** (0.067)	0.512*** (0.098)
Observations	2150	687	786	677	737
Test of equality of Free coefficient w.r.t.					
Panadol	0.006	N/A	0.099	0.010	0.000
Elyzole	0.788	0.099	N/A	0.330	0.029
Zinkid	0.258	0.010	0.330	N/A	0.129
Mean of NGO*Sale	0.845	1.720	0.688	0.312	0.714
Mean of For-Profit*Free	0.729	1.363	0.495	0.240	0.762
p-value of Free = 0	0.004	0.005	0.116	0.302	0.367
p-value of Free + Free*NGO = 0	0.198	0.754	0.031	0.607	0.370

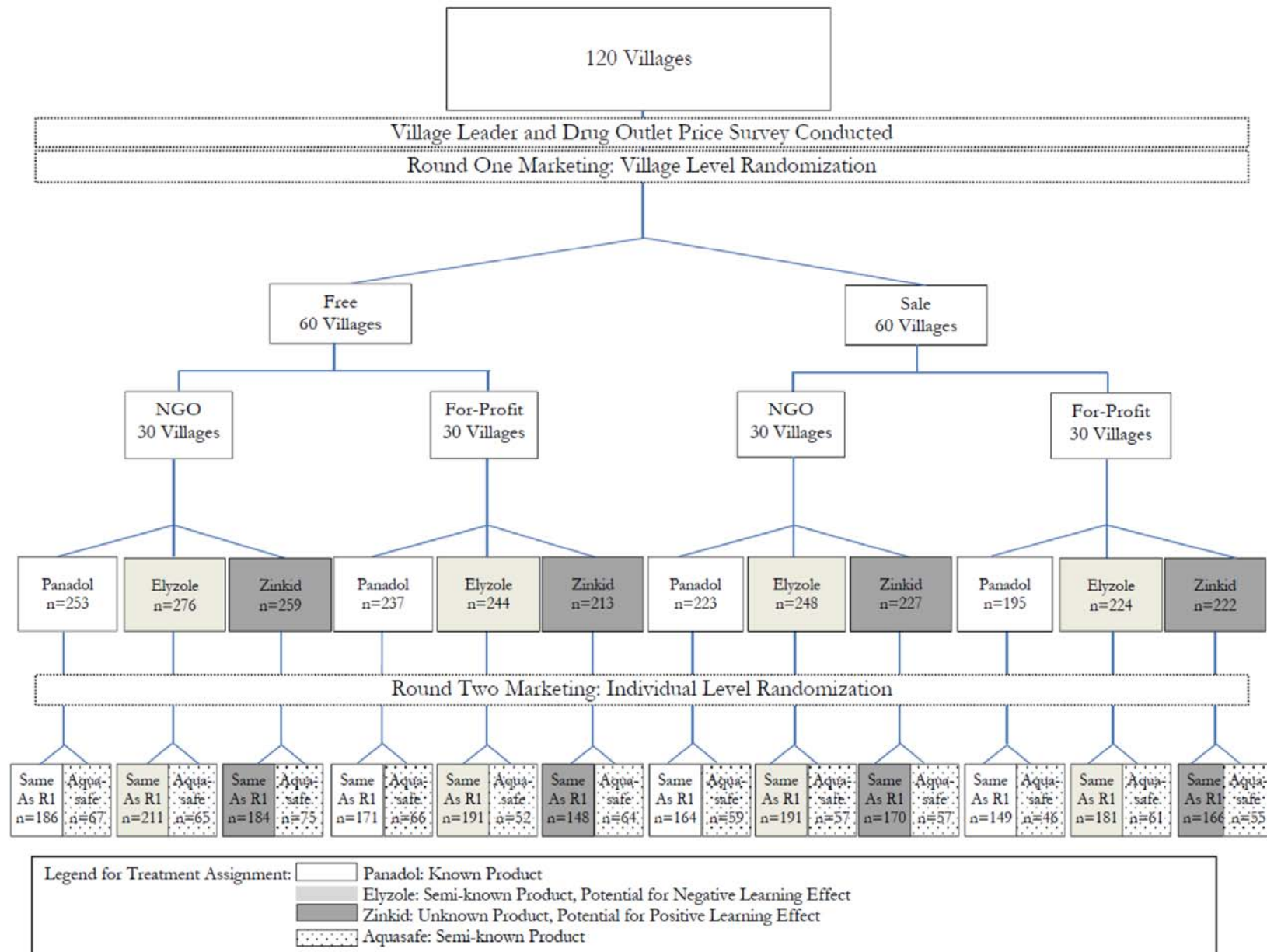
Village assignment to treatment was block randomized according to two variables. The first, *price environment*, included information about pricing and drug availability with three possible categories: (1) no drug outlets or none of our drugs; (2) no prices above the median or distributed for free; and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

Table 5: Observed Usage Summary Statistics

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

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

Figure A1



A Derivations and proofs

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

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

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) Enumerator Name: _____

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

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

Before filling in this form, you must:

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

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

- 1) Did the respondent make a purchase? Yes No

If 'Yes' move to Question 2.

If 'No' move to Question 3.

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

- a. Can you tell me more about why you bought this product? *CIRCLE ALL THAT APPLY*

1---I ran out of my supply _____

2--- I trust you (*ASK WHY AND WRITE ANSWER OPPOSITE*) _____

3---The price is cheaper than what I can get it for here _____

4--- I want to sell it on to others _____

5--- I would have to travel far to find this elsewhere _____

6--- I want it in case someone becomes sick _____

7---Other (FILL IN OPPOSITE) _____

99--- Didn't answer

- b. For whom did you buy this for? *CIRCLE ALL THAT APPLY*

1--- Myself

2--- Adults

3---Grandparents / Elderly

4---Children/babies

4---Other: _____

99-- Didn't answer

- c. When do you expect to start using the product?

1---This week

2--- Next week

3---In the next month

4---In the next 2-3 months

5---6 months or more

6--- Other _____

99--- Didn't answer

- 3) [If did not make a purchase] Can you tell me more about why you did not buy this? *CIRCLE ALL THAT APPLY*

1--- I got it for free previously, why should I buy it now?

7--- I need to ask my spouse.

2--- Other people in this village have previously got it for free.

8--- I don't trust you or I'm uncomfortable buying this from you.

3--- I'd like to buy it, but don't have the money here.

9--- Don't know

4--- I think it is too expensive.

10--- Didn't answer

5--- It's not essential.

11--- Other: _____

6--- I already have enough of it.

99--- Didn't answer

- 4) [Ask everyone] Is this the type of product that people in your village would resell or trade?

1---Yes If yes, how much do you think they could sell/trade it for? | _____ | UGX --or--- Item to trade with: _____

2---No

99--- Didn't answer

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