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ELICITING AND UTILIZING WILLINGNESS TO PAY: EVIDENCE FROM FIELD TRIALS IN NORTHERN GHANA[†]

Abstract

We demonstrate the benefits and feasibility of using the Becker-DeGroot-Marschak (BDM) mechanism to elicit precise, individual-level willingness to pay and thereby enhance the information generated by randomized experiments. With a relatively small sample and minor modifications to a standard field experiment design, we can directly estimate demand, study the effect of prices on usage through screening and psychological (sunk-cost) effects, and compute heterogeneous marginal treatment effects. Applying the mechanism to a field experiment studying clean drinking water technology in northern Ghana, we show that even in an environment with low literacy and numeracy, BDM produces sensible results. We find that although willingness to pay for clean water technology is low relative to the cost, demand is surprisingly inelastic at low prices; prices do not generate significant sunk-cost effects; and treatment effects are heterogeneous with respect to valuation and consistent with outcomes being affected by effort expenditure.

JEL Classification: C26, C93, D12, L11, L31, O12 and Q51
Keywords: field experiments, health behavior, heterogeneous treatment effects and price mechanism

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1 Introduction

Economists, firms, and policymakers are often interested in knowing how much an individual is willing to pay for a good, service or amenity. The answer to this question is, of course, the fundamental building block of demand functions and hence our ability to estimate demand elasticities and consumer surplus. Practically, such measures can inform pricing policy, guiding the magnitude and targeting of discounts or subsidies. They also provide an important intermediate input for the study of technology adoption, social learning, and other issues related to demand formation. Willingness-to-pay and its relationship to a product's benefits are critical for understanding when the price mechanism is useful for allocating goods where their benefits are greatest and when it simply limits access for those with the greatest need.[1] Moreover, willingness to pay provides a link between the structural and treatment effect approaches to policy evaluation and, since price is often a policy variable dimension of interest, is a natural dimension along which to assess heterogeneous treatment effects.[2]

Ideally, one would like a precise measure of each individual's willingness to pay (WTP); however, obtaining such a measure is often difficult. If an individual believes her answer to the question, "How much are you willing to pay for this product?" will affect the actual price, she may answer strategically. Alternatively, her answer to a hypothetical question may differ substantially from what she would actually do when confronted with a real-money choice. Economists have considered a range of techniques to elicit a truthful answer, including various stated-preference methods such as contingent valuation and conjoint analysis (Carson and Hanemann, 2005), and revealed-preference methods such as simple take-it-or-leave-it offers, Vickrey auctions, and *n*th-price auctions (Shogren, 2006). In field experiments, demand is often measured using take-it-or-leave-it (TIOLI) offers, sometimes at randomized prices. TIOLI is transparent and simple to implement, but provides limited information, since the researcher only observes an individual's

[1] See, for example, Ashraf, Berry and Shapiro (2010), Cohen and Dupas (2010), Karlan and Zinman (2008), and Tarozzi et al. (2014).

[2] See Heckman and Vytlacil (2005); Heckman, Urzua and Vytlacil (2006); and Chassang, Padró i Miquel and Snowberg (2012).

binary decision to buy or not buy at a single price point. The Becker-DeGroot-Marschak mechanism (BDM), commonly used in experimental economics, provides an attractive and underutilized alternative. In contrast to TIOLI, BDM elicits an individual's exact willingness to pay for a good. It operates much like a second-price auction against an unknown or random price. An individual states her bid for an item, then a random price is drawn from a distribution. If her bid greater than or equal to the price, she receives the item and pays the price drawn. If her bid is below the price, she pays nothing and receives nothing. For expected utility maximizers, whose preferences over lotteries can be summarized by their certainty equivalent, bidding one's true maximum willingness to pay is the dominant strategy.[3]

Between October 2009 and June 2010, we used both BDM and TIOLI to study the willingness to pay for and impacts of household water filters in a sample of 1,266 subjects from 15 villages in rural northern Ghana. The setting is appropriate for our study, as a high incidence of diarrheal disease and lack of infrastructure for improved drinking water sources has led to promotion of point-of-use water treatment through social marketing. The filter requires effort to use, but if used properly can reduce diarrhea among adults and children who drink from it. After normal marketing efforts, we elicited willingness to pay and distributed the filters. We conducted two follow-up surveys after one month and one year to measure filter usage and health outcomes related to water quality.

We use our experiment to demonstrate three properties of the BDM mechanism that make it appealing for field work. First, by providing a precise measure of willingness to pay, it allows for direct, non-parametric estimation of demand. This feature allows us to inform pricing policy with direct predictions for take-up at all potential prices, rather than a fixed set of prices implemented under TIOLI.[4] In our experiment, we find nearly all households are willing to pay something for the filter; however, the median WTP is only 10-15% of the cost of manufacturing and delivery.

[3] As demonstrated by Karni and Safra (1987) and Horowitz (2006), BDM is not necessarily incentive-compatible for non-expected utility maximizers, a feature it shares with auctions.

[4] Note that the standard BDM mechanism estimates demand for only single unit-demand items, such as the water filter studied in this project. By modifying the mechanism to elicit the willingness to pay for additional increments of the good, BDM can be used to estimate demand for products where multiple units may be demanded by a single individual. See Hoffmann (2009) for an example.

Second, BDM induces random variation in both treatment status and price paid conditional on willingness to pay. This allows the researcher to separately identify selection—those with a higher WTP for a product may be more likely to use it or have a greater benefit—and psychological or sunk-cost effects. These effects are typically difficult to disentangle, even with randomized prices, since an observed relationship between price and use among those who purchase at that price could include both effects.[5]

Combining BDM with survey data on filter use, we find some evidence of a modest screening effect: use at the one-year followup increases slightly with WTP over most of the distribution of WTP. We find no evidence that price paid has a causal (sunk-cost) effect on use: conditional on one's willingness to pay, the price paid does not affect usage or outcomes.

Third, BDM generates detailed information on heterogeneous treatment effects with respect to willingness to pay (Heckman et al., 2006; Heckman and Vytlacil, 2007). Like TIOLI methods with random prices, BDM provides an exogenous source of variation in product allocation, allowing researchers to identify treatment effects of the product. But unlike TIOLI, BDM allows researchers to easily estimate heterogeneous treatment effects, i.e., whether and how treatment effects vary with willingness to pay. Intuitively, BDM reveals each individual's willingness to pay and then allocates the good to her randomly, conditional on that willingness to pay. We demonstrate how BDM can allow researchers to estimate the distribution of marginal treatment effects in a variety of field settings.[6] In our particular context, we find that the filter's benefits, as measured by reductions in diarrhea among children, increase with WTP over most if its distribution, consistent with the pattern of usage.

Balanced against these advantages, BDM faces a number of challenges. It is a novel mechanism with limited experience outside the lab. Moreover, our study presents a severe test of BDM. Numeracy among our subject pool was low and non-standard beliefs about probability were com-

[5]One approach, pioneered by Karlan and Zinman (2009), is a two-stage randomization: first, a random initial offer price; second, a surprise discount after the subject has made her purchase decision. BDM generates this two-stage randomization, but does not require the second stage to be a surprise. It can therefore be implemented effectively in environments where individuals know or are likely to discover the allocation mechanism independently.

[6]The ability of BDM to improve information extraction from randomized control trials is emphasized by Chassang, Padró i Miquel and Snowberg (2012), who describe BDM as an example of a "selective trial."

monplace. We find that even in this setting, subjects were able to readily grasp the mechanism and provided sensible answers.

There is a substantial literature dealing with the implementation and behavior of BDM in university economics labs; however, little is known about the practical applicability of BDM in a field setting.[7] To explore this issue, we randomly assigned respondents to be offered a water filter using either BDM or TIOLI. Results from both methods of demand elicitation follow a similar pattern; however, TIOLI acceptance rates were above the BDM-estimated demand curve.[8] While actual demand depends on the distribution mechanism, we remain agnostic about whether BDM or TIOLI provide the more accurate estimates of market demand and are encouraged by the demonstrated feasibility of BDM to enrich the information generated by randomized control trials.

The rest of the paper proceeds as follows. Section 2 provides background on clean drinking water. Section 3 explains the experimental setting and implementation. Section 4 describes the use of BDM for demand estimation and evaluates the correlates of willingness to pay. Section 5 explores the causal effects of price paid as well as the relationship between willingness to pay and use. Section 6 illustrates the use of BDM to estimate heterogeneous treatment effects. Section 7 concludes.

2 Background

Lack of access to clean water is one of the most significant threats to health and welfare in the developing world, particularly rural Africa. Nearly 40 percent of Africans—and 52 percent of

[7] See, for example, Smith (1982), Keller, Segal and Wang (1993), Bohm et al. (1997), Irwin et al. (1998), Noussair, Robin and Ruffieux (2004), Mazar et al. (2014) and Cason and Plott (2014). Hoffmann, Barrett and Just (2009) use BDM to measure the gap between willingness to pay and willingness to accept for bed nets in Uganda. Other recent applications include Cole and Fernando (2012), Cole et al. (2014), Guiteras and Jack (2014), Guiteras et al. (2014a), and Guiteras et al. (2014b).

[8] There are a number of reasons why BDM may yield lower willingness to pay than the TIOLI mechanism. First, respondents may believe that they can influence the future price of the item by bidding low. Second, the TIOLI offer may anchor respondents to a valuation that is higher than what they would bid in the BDM mechanism. Respondents may believe that the stated price carries some information about a product (Wolinsky (1983); Milgrom and Roberts (1986); Ashraf, Jack and Kamenica (2013)). Take-it-or-leave-it offers can themselves be unusual in environments where fixed, posted prices are rare and bargaining common.

rural Africans—lack access to improved sources of drinking water. This has serious health consequences: diarrheal disease causes nearly 1.8 million deaths worldwide each year and is responsible for 17 percent of deaths of African children under five years of age. Poor water quality also harms the health of the living, contributing to diseases such as schistosomiasis, trachoma and worms. In Ghana, 26 percent of rural households lack access to clean water, and diarrheal diseases are the third leading cause of death for children under five years of age (World Health Organization, 2004, 2011).

Absent improved water sources, a variety of free and socially-marketed point-of-use purification methods have been distributed and sold to households (Clasen et al., 2007). We study the *Kosim* water filter (see Figure A1 in the Appendix), marketed and sold in northern Ghana by Pure Home Water, a non-governmental organization. The filter is highly effective at improving water quality and is appropriate for this context, since it removes particulates and pathogens from water without the use of chemicals or electricity (Miller, 2012). At the time of the study, the average cost of producing a filter and delivering it to a rural household in a village-level distribution was approximately GHS 21 (about $15). Demand for the filter is effectively zero at a break-even price, so the level of subsidy to provide, and consequently the relationship between price and access, use, and outcomes are key concerns for an NGO with a limited subsidy budget.

We offered the filter to 1,266 respondents across 15 villages in northern Ghana between October 2009 and June 2010. To select our sample, we identified villages in Northern Region of Ghana that had limited access to clean drinking water and had not previously been exposed to the *Kosim* filter. Within our study villages, we conducted our baseline survey and sales exercise with all primary caregivers of children age 12 or younger. These were primarily mothers, but occasionally were other relatives caring for children whose parents had migrated, were deceased or were permanently absent for other reasons.[9]

[9]Most subjects live in extended patrilineal family compounds, which are small clusters of individual huts, usually enclosed by a wall. Many resources are shared within the compound, although in most cases each woman is responsible for providing water for her own husband and children. As described below, the sales mechanisms were randomized at the compound level and all inference is robust to clustering at the compound level.

3 Experimental Setting and Design

3.1 Data Collection and Experimental Setup

3.1.1 Preliminary Activities & Household Survey

MARKETING MEETING. In each study village, we first conducted an initial village meeting, during which we provided a demonstration of the filter and the BDM and TIOLI sales mechanisms, following closely the standard practice of our evaluation partner. Two field staff performed a mock version of both BDM and TIOLI for a token item, such as chocolates or a bar of soap. The field staff also practiced the sales mechanisms with volunteers from the attendees, again for a token item. We informed villagers that a filter would be installed at the village health liaison's home and encouraged them to visit the liaison to see the filter working, taste the water and ask questions. We instructed the attendees that we would visit their households in approximately two weeks to offer them an opportunity to purchase the filter via one of the mechanisms we performed. Attendees were encouraged to discuss with their families what they were willing to pay for the filter. The two-week interim period was consistent with standard sales and marketing practices for the product and was chosen to allow families time to try the filter, determine their WTP, and obtain necessary funds.

On the same day as the marketing meeting, we conducted a comprehensive census of all residents of the village. With this information, we were able to identify the study subjects as defined above and perform random assignment of the sales mechanisms.

WATER QUALITY TESTING. Roughly one week after the village presentation and census, we visited each household to remind them of the upcoming sales visit and to answer any questions they had about the filter. During this reminder visit, we took a 100 ml baseline sample of their stored drinking water for testing in the lab. Half of the samples were randomly selected to be tested for levels of *E. coli* and turbidity.[10]

[10]Logistical constraints prevented testing all water samples. In addition, we conducted one of two health education treatments in randomly selected households. The first treatment was a general message describing the link between untreated water and health and explaining how the filter helps prevent diseases such as diarrhea. The second treatment

HOUSEHOLD SURVEY. Roughly one week after the reminder visit, we conducted a survey and sales visit with each respondent. Respondents were compensated with a GHS 1 cash gift, awarded at the beginning of the survey.[11] All respondents were administered a basic survey covering demographic information, asset ownership, and education status. The baseline survey also elicited information on water collection and treatment practices, basic health knowledge, and recent episodes of diarrhea among household members.

3.1.2 Filter Sale / BDM Implementation

At the end of the survey, we conducted the sales experiment.[12] Respondents were randomly assigned in equal proportions to either a BDM or TIOLI sales treatment.[13] Sales treatments were randomly assigned at the compound level, stratified by number of respondents in the compound.[14]

The scripts for the sales were designed to be identical across treatments apart from the specific sales mechanism. Each sale began with a practice round for a bar of soap with retail value of approximately GHS 1. The respondent was then given the opportunity to purchase the soap using the mechanism corresponding to her treatment group. After the practice round was complete, the respondent was given the opportunity to purchase the *Kosim* filter using the same mechanism.[15]

BDM TREATMENT. First, the surveyor read a brief description of the BDM procedure. We emphasized that the respondent would have only one chance to obtain the filter, could not change her bid after the draw, and must be able to pay that day. The surveyor then played a practice

provided similar health information but emphasized the dangers to children of untreated water and the potential benefits of the filter to children. The impacts of these treatments on WTP were minimal and are discussed in the Supplementary Materials.

[11] This was awarded in small denomination coins to ensure that respondents could submit reasonably fine-scale bids in the practice WTP game described below. It is possible that a cash gift influenced WTP for the filter by inducing goodwill toward the surveyor. However, because of the length of the survey there was always at least 30 minutes between the gift and the sales offer, which could ameliorate any "house money" effect.

[12] By conducting the sale at the end of a survey on water and health, we may have primed the respondent's demand for the filter. However, it was not feasible to conduct the sale first, because respondents, and especially respondents who were not able to purchase the filter, would quickly lose interest in the survey.

[13] Within each of these two broad categories, we conducted three sub-treatment to understand how the sales mechanism might affect strategic behavior or anchoring effects. These sub-treatments did not generate substantial differences within either mechanism, and we group them together for the main analysis. See the Supplementary Materials for a discussion and analysis of these sub-treatments.

[14] Compounds with three or more respondents were grouped into a single stratum.

[15] Complete scripts for the BDM and TIOLI treatments are provided in the Supplementary Materials.

round for the bar of soap. The respondent was asked for her maximum WTP for the bar of soap. The surveyor reminded her that if she drew slightly more than her bid, she would not be able to purchase the soap. She was then allowed to adjust her bid. This process repeated until she was no longer willing to adjust her bid. At this point, the surveyor reminded her that if she drew a price equal to her bid she must be willing and able to make this payment. Before the random price was drawn, the surveyor reviewed various hypothetical outcomes to test her understanding. Once the final bid was established, the price was drawn and the subject either purchased or did not purchase the soap in accordance with the BDM mechanism.[16]

The procedure for the filter was similar; however, at the completion of the sales process, the respondent, if successful, paid for the filter and received a receipt that could be redeemed for at a central location in the village, typically the health liaison's home.[17]

We did not require respondents to present the amount of cash they were willing to bid before the draw was made. Rather, we permitted the household to gather the money by the end of that day. Before the draw was made, we asked multiple times whether the respondent would have access to the funds. We did this to maintain realism: households routinely make small loans to each other for purchases. Of the 272 respondents who drew a price less than or equal to their bid, 269 (98.9%) completed the purchase. For the three respondents who did not, their failure to purchase appears to have been due to an inability to gather funds, e.g., because a family member was unavailable, rather than some misunderstanding of the mechanisms.

We also tracked whether a losing respondent attempted after the fact to purchase at the price drawn (i.e., above her final offer) and asked all losing respondents whether they wish they had

[16]This protocol was based on extensive piloting of different procedures to maximize understanding in this population. Although developed independently, our protocol is similar to the "titration BDM" mechanism tested by Mazar, Koszegi and Ariely (2014). Prices were written on wooden beads and placed in an opaque cup. The subject draws the price herself. The prices were distributed uniformly from 0 to 100 in increments of 10 pesewas (GHS 0.10). We did not inform subjects about the distribution of prices.

[17]The distribution of prices was 0, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 5, 6, 7, 8, 9, 10, 11, 12 in equal proportions. The most salient difference between the procedure for the filter and for the practice round was that the filter was not physically present in front of the respondent during the bidding. We chose not to have surveyors bring the filters to compounds for two reasons: first, they are bulky and could break; and second, there is some instruction on assembly and care that should be given at the time the household receives the filter. This instruction was most efficiently provided at a central location.

bid more. A substantial share (19.2 percent) exhibit ex post regret, stating that they wished they had bid more.[18] However, only 5.4 percent (18 of 331) actually offered to pay more than their final bid. Taken together, these results suggest that even in an environment with very low literacy and numeracy, the BDM mechanism, with suitable modifications, can be readily understood and incorporated into field experiments. Based on pilot results, we believe that multiple demonstration rounds with a different product or products and the understanding check after respondents stated their bids are essential to successful implementation.

TIOLI TREATMENT. The standard take-it-or-leave it treatment was a simple sales offer at a randomized price. Similar to the BDM treatment, we first conducted a practice round for a bar of soap. We then presented the offer for the filter randomized in equal proportions across three prices: GHS 2, 4, and 6.[19] These prices were the approximate 25th, 50th and 75th percentiles of BDM bids in pilots in similar villages. Before revealing the offer price to the respondents, we emphasized that there would be no bargaining. If they accepted the offer price, respondents were allowed until the end of the day to obtain the necessary cash. If the respondent initially agreed to the purchase but was ultimately unable to obtain the funds, we code her as not purchasing.

3.1.3 Follow-up Surveys

Two follow-up surveys were conducted approximately one month and one year after the initial sale. Each survey measured whether households had retained the filters they purchased, whether the filters were being used and maintained properly, and recent diarrhea episodes of children aged 5 and under. The one-month follow-up survey was conducted with all households that had been surveyed at baseline. Due to funding constraints, we randomly selected eight of the original 15 study villages to be included in the one-year follow-up survey.

[18] We find that ex post regret is highest for those who narrowly missed winning in BDM. Roughly 40 percent of those who missed by GHS 1 or less wished that they had bid more, with this percentage declining to approximately 12 percent among those who missed by GHS 5-10.

[19] As described above, the TIOLI treatment was divided into three sub-treatments. Approximately one-third of respondents received a sub-treatment where soap and filter prices were determined by a draw from a cup. For the remaining respondents, the soap and filter prices were randomly assigned at the compound level. The Supplementary Materials discuss the sub-treatments in detail.

3.2 Sample Characteristics and Balance

Table 1 displays summary statistics of the sample and analysis of balance of the randomizations. Column 1 displays means of baseline characteristics for the full sample. Only 9 percent of respondents had ever attended school, and the average number of children aged 0 to 5 was 1.3 per respondent. Diarrhea incidence was relatively high: on average, households had 0.24 episodes of diarrhea among children aged 0 to 5 in the past two weeks. Only 19 percent of households had access to an improved water source year round.[20]

Columns 2 and 3 of Table 1 display the sample means by treatment (BDM vs. TIOLI), and Column 4 displays the difference in means between the two treatments groups. We observe a few marginally significant differences between the two groups: 0.16 more children aged 0 to 5 per household in the BDM treatment ($p < 0.1$), 0.13 fewer children aged 6 to 17 ($p < 0.1$), 0.07 fewer children aged 0 to 5 with diarrhea in the past two weeks (p<0.1), and 0.45 fewer men in the compound ($p < 0.1$).

In Column 5 of Table 1, we check the balance of the BDM draw randomization by regressing the BDM draw on the same set of characteristics as well as the BDM bid. Of the 13 variables in the regression, one is significant at the 10 percent level: a higher number of women in the compound is associated with a slightly higher draw. Column 6 of Table 1 regresses the TIOLI price on baseline characteristics. Here, higher assigned prices were associated with fewer women in the compound ($p < 0.1$), more children aged 6 to 17 with diarrhea in the past two weeks ($p < 0.1$), and higher turbidity in stored water ($p < 0.01$).

[20]Due to logistical limitations, water quality data (*E. coli* counts and turbidity measures) was measured for only half of the sample. Since households were randomly selected for water quality testing, this explanatory variable data is, by design, missing completely at random (MCAR). For simplicity, we incorporate into the regression models an indicator variable for whether or not a variable is observed. As demonstrated by Jones (1996), this method can still yield biased estimates even when data are MCAR. Complete-case analysis (i.e., using only those observations without missing water quality measures) is unbiased, but throws away data. We use the complete-case data to estimate bounds on the potential bias in the indicator method. Due to low pairwise correlation between water quality measures and other explanatory variables, these potential biases are small and do not alter the economic or statistical significance of estimates. All results are robust to multiple imputation (Rubin, 1996).

4 Willingness to Pay, Demand and Correlates

This section describes the advantages of using BDM to elicit each individual's willingness to pay, presents the results of our demand estimation, evaluates the correlates of willingness to pay, and compares results to those obtained by TIOLI. Many of the benefits of BDM stem from its ability to provide an exact value for WTP for each individual, with precision limited only by the desired granularity of the researcher.[21] In contrast, a TIOLI offer provides only a bound. For example, if a respondent accepts a TIOLI offer of GHS 4, we can only conclude that her WTP was at least GHS 4. Similarly, if she rejects an offer of GHS 6, we can only conclude that her WTP was less than GHS 6. BDM's precision allows for direct, nonparametric estimation of demand at all potential prices and facilitates estimating relationships between WTP and important observables, e.g., wealth and health status. In large populations, this is primarily an issue of sample size, albeit a significant one; however, BDM can also be employed effectively in relatively small sub-population to estimate, for example, heterogeneous responses to health education programs or social learning at the village level.[22]

Auctions can also provide precise data on WTP; however, unlike auctions BDM is robust to intra-community conflict or collusion and allows individuals with low WTP to receive the good with positive probability. By varying the price distribution, the researcher can target any desired probability of receiving treatment, subject only to preserving incentives for truthful reporting of preferences.[23]

[21] In principle, it is possible to measure exact maximum WTP down to the smallest available denomination. For example, respondents in our study were free to bid in increments of pesewas (1/100th GHS); however, in practice most final bids were in increments of 50 pesewas (GHS 0.5).

[22] Nonparametric estimation of P points on a demand curve at a desired level of precision requires a TIOLI sample approximately P times larger than what is required using BDM. Alternatively, for a fixed sample size, TIOLI confidence intervals at each point will be wider by a factor of approximately $\sqrt{P}$.

[23] Truthful reporting constitutes a unique optimum if and only if an individual's WTP is in the support of the price distribution. If she believes that all prices are above or below her WTP, she will have no incentive to bid precisely her WTP. Similarly, if the gap between prices is wide, a subject need not reveal her exact WTP between two prices.

4.1 Estimating Demand

Figure 1 shows the inverse demand curve generated across all 15 villages using data from the 608 BDM respondents. At each point along the x-axis, we plot the share of BDM subjects whose bid was greater than or equal to p, along with a point-wise 90%-confidence band robust to clustering within compound. The average bid was GHS 3.0 with a median of GHS 2.5.

There are several features of this inverse demand curve worth noting. First, WTP is almost universally positive: nearly 95% of respondents bid at least GHS 1. At the same time, WTP is low relative to the cost of the filter: the median bid of GHS 2.5 corresponds to approximately 10-15% of the cost of manufacturing and delivery. This result is consistent with the relatively low willingness to pay for water treatment and other health goods found in previous work (Kremer and Holla, 2009; Ahuja et al., 2010); however, demand at low prices is substantially less elastic than has been observed in other settings.[24]

For comparison, Figure 1 also displays the share of TIOLI subjects who purchased at each of the three, randomly assigned TIOLI price points. As with BDM, the 90%-confidence intervals are robust to clustering within compound. The pattern of demand is consistent across the two mechanisms, but we note that despite their theoretical equivalence at each of the TIOLI price points the purchase rate is above what would be predicted by the BDM demand curve.[25]

4.2 Correlates of Willingness to Pay

Understanding the relationship between WTP and household characteristics can inform how pricing policies target particular types of households. In this section we demonstrate the use of BDM to estimate this relationship directly and show that BDM-elicited valuations display sensible correlations with several key characteristics. Previous studies have found limited evidence that higher WTP for health goods is related to health characteristics or wealth (Ashraf, Berry and Shapiro,

[24] Other studies of health goods in developing countries have found mixed evidence of price sensitivity at zero: Kremer and Miguel (2007), Kremer et al. (2009) and Cohen and Dupas (2010) find that demand falls sharply at any positive price, while Ashraf et al. (2010) and Cohen et al. (2015) find less sensitivity at zero.

[25] See the Supplementary Materials for further comparison of TIOLI and BDM and an exploration of potential differences.

2010; Cohen and Dupas, 2010; Cohen, Dupas and Schaner, 2015). This is a common problem in the consumer behavior literature: heterogeneity in choice is only weakly correlated with standard consumer attributes (Browning and Carro, 2007; Nevo, 2011).

We model the relationship between WTP and baseline characteristics and behaviors as

$$\text{WTP}_{ic} = \alpha_0 + X_{ic}^{'}\beta + \varepsilon_{ic}, \tag{1}$$

where X_{ic} is a vector of characteristics of interest for subject i in compound c, and ε_{ic} is an error term, possibly correlated at the compound level. We consider a variety of characteristics and behaviors. First, we include variables relating to household demographic composition (number of adult males and adult females in the compound, subject's number of children aged 0 to 5 and 6 to 17), an indicator for whether the subject has attended school, and a wealth index (the first principal component of a set of variables on ownership of durables, land and livestock). Second, we include two variables that indicate the number of children aged 0 to 5 and 6 to 17 who have had diarrhea in the past two weeks. Finally, we include four variables relating to access to improved water, water treatment practices, and water quality.

Estimating Equation 1 using our BDM sample is straightforward: we run an ordinary-least-squares regression of the BDM bid on the vector of characteristics. Column 1 of Table 2 presents the results of this regression. The BDM bid is positively related to the number of children 0 to 5 with diarrhea, a result significant at the 10-percent level. One additional child with diarrhea in the household (conditional on the total number of children), increases the BDM bid by GHS 0.57. The BDM bid is also positively related to durables ownership (significant at the 10-percent level), and negatively related to turbidity (significant at the 5-percent level).[26] The p-value of the F-test of the regression equals 0.024, indicating observable characteristics are jointly significantly related to BDM-measured WTP.

[26]The correlations with children's health status and asset ownership are as one would expect. The turbidity result suggests that household with clearer water have higher WTP. We interpret the latter result as an indication that households who let their water settle, access cleaner appearing sources, or use other methods to remove turbidity have higher demand for the filter. During the marketing phase, households are told that the filter will require more frequent cleaning if using turbid water.

These results show that, at least in this context, households' health and wealth influence their willingness to pay for health products. By generating precise, individual WTP measures BDM facilitates discovery of these correlations; however, we note that, consistent with the aforementioned consumer behavior literature, much of the heterogeneity across subjects remains unexplained.

For comparison, we conduct the analogous exercise using TIOLI subjects, estimating a binary discrete choice model via probit. For respondent i assigned price p, we observe

$$\text{buy}_{i,p} = 1\left\{\text{WTP}_i \geq p_i\right\} = 1\left\{\text{WTP}_i - p_i \geq 0\right\} = 1\left\{\alpha_0 + X_{ic}^{'}\beta + \varepsilon_{ic} - p_i \geq 0\right\}. \tag{2}$$

where $\text{buy}_{i,p}$ is an indicator equal to 1 if respondent i agreed to buy when assigned price p. We normalize the coefficient on price to -1, so that the estimates of the coefficients β are directly interpretable in terms of WTP and are comparable to those obtained by estimating Equation 1 with BDM subjects. Results for the TIOLI subjects are presented in Column 2 of Table 2, with estimated differences between BDM and TIOLI in Column 3.[27] In the TIOLI sample, most of the estimates are statistically indistinguishable from zero, but, notably, the variable indicating children aged 6 to 17 in the household with a recent diarrhea episode has a significantly *negative* association with WTP. The corresponding variable for younger children is also negative but not significant. As shown in Column 3, there are a few significant differences between the estimates for BDM and TIOLI. In the cases where coefficients differ significantly, the BDM coefficient conforms more closely to our prior beliefs. For example, we expect health concerns to be more salient to educated parents and to parents whose young children had more recently had diarrhea. We are unable to explain why the pattern of correlations differs across these two mechanisms and believe further work along this dimension may be helpful in understanding heterogeneity in consumer demand.

[27] To test for differences in the estimated β, we estimate Equations 1 and 2 as a system using seemingly unrelated regression.

5 Screening and Sunk-Cost Effects

The BDM mechanism embeds a double randomization that allows researchers to separately identify two factors that may be important for pricing policy: the *sunk-cost effect*, i.e., the causal effect of price paid conditional on WTP, and the *screening effect*, i.e., the correlation between WTP and use. Because the price draw is random, we can test for causal effects of price paid by comparing measures of use for subjects with the same WTP but who paid different prices. Similarly, we can test for screening effects by comparing use for subjects with different WTP while controlling, if needed, for price paid. For example, BDM generates the following experiment: consider three subjects, each willing to pay GHS 6 for a filter; one doesn't receive the filter; another pays GHS 6; and the other pays GHS 2. Thus, at every level of WTP above the minimum price, there is variation in both allocation and the price paid conditional on allocation. In this section, we illustrate the usefulness of this feature using the two waves of followup data collected approximately one month and one year after the filter sale. We find no evidence of a causal effect of price paid and modest evidence of a positive association between use and WTP.

We collected three objective indicators of use from all subjects who purchased the filter: (i) whether the filter was found in the compound and was undamaged; (ii) whether water was in the plastic storage reservoir; and (iii) whether water was in the clay filter pot. These measures are normalized and aggregated into a single usage/effort index following Kling, Liebman and Katz (2007).

To test for a causal effect of price paid, we estimate

$$\text{use}_{ic} = \alpha_0 + \alpha_1 D_{ic} + \alpha_2 f(\text{WTP})_{ic} + \varepsilon_{ic}, \tag{3}$$

where use_{ic} represents the usage measure, D_{ic} is the respondent's draw, and $f(\text{WTP})_{ic}$ is a cubic polynomial of bid. It is important to control adequately for WTP since, although the price draw was unconditionally random, conditional on receiving the filter it is positively correlated with WTP.

Table 3 presents results from OLS estimation of Equation 3. Panel A shows that there is no

detectable effect of the price paid on use in the one-month followup. Panel B shows a similar null result in the one-year followup data. Taken together, this suggests there is no significant sunk-cost effect.

We next turn to the relationship between WTP and usage in the BDM treatment.[28] We perform this analysis in two ways. First, we regress usage measures on BDM bid among those who purchased the filter. Given the absence of evidence for causal effects of price paid reported above, our primary specification does not control for price paid. The results of these regressions are shown in Table 4. In the short term, use is generally high and there is no evidence for an association between WTP and use. At the one year follow-up, GHS 1 of higher WTP is associated with a 2.7 percentage point higher likelihood of having water in the plastic storage vessel ($p < 0.10$). WTP is positively associated with a higher level of the aggregated use index, but this association is not statistically significant.

Second, we model the relationship between usage and WTP non-parametrically for comparability with our analysis of heterogeneous treatment effects in Section 6 below. We restrict the sample to households with children aged 0 to 5 and estimate the relationship between WTP and the usage indices using kernel regression. Figures 2a and 2b graph this relationship in the one-month and one-year follow-up surveys, respectively. Using the one-year data (Figure 2b), we observe a pattern of increasing usage with respect to WTP over most of the distribution. This pattern is similar to that of the one-year treatment effects, discussed below.

6 Heterogeneous Treatment Effects

6.1 Theory

By eliciting respondents' willingness to pay and allocating treatment randomly conditional on this value, BDM provides an easily implementable way to recover the marginal treatment effects (MTEs) introduced by Björklund and Moffitt (1987) and extended by Heckman and Vytlacil (2005,

[28] The relationship between WTP and usage in the TIOLI treatment is described in the Supplementary Materials.

2007). The intuition is analogous to that of the structural approach developed developed in the prior literature. At each level of WTP, individuals are randomly assigned to either receive the product or not. However, the structural approach requires estimation of a selection equation and then calculating MTEs with respect to a predicted probability of treatment; with BDM we can simply use the price draw as a local instrumental variable conditional on the elicited WTP.

This section describes how we can use this instrument to estimate the distribution of MTEs across the support of the WTP distribution. As Heckman and Vytlacil (2005) detail, the policy object of interest is not always represented by the local average treatment effect from a linear instrumental variable. In our setting, it may be that those who are likely to benefit the most from a product are aware of this and have the resources to pay for it, in which case charging for the product targets those with higher treatment effects (Cohen et al., 2015). On the other hand, it may be that individuals who are most likely to benefit are either unaware of the extent to which they will benefit or are simply too poor or too credit constrained to purchase the product, in which case higher prices will likely restrict access without improved targeting (Cohen and Dupas, 2010). Once we have estimated the distribution of MTEs, the distribution can be integrated with different weights to answer different policy questions. Since price is a natural policy variable in this setting, recovering the distribution of MTEs with respect to willingness to pay allows one to easily perform counterfactual policy experiments such as evaluating targeted subsidies or free distributions.

With BDM, this exercise is relatively straightforward. Consider the following outcome equation:

$$y_{jic} = \beta_0 + \beta_1 T_{ic} + u_{jic}, \tag{4}$$

where y_{jic} is the outcome of interest (an indicator for one or more cases of diarrhea in the previous two weeks) for child (aged 0 to 5) j of subject i in compound c, T_{ic} is an indicator for whether subject i purchased a filter, and u_{jic} represents unobservable determinants of health. We suppress covariates for brevity. The classic identification problem comes from the fact that u_{jic} is likely to be correlated with T_{ic}. Unobservable attributes or behaviors affecting child health may be different on average between households that buy or do not buy a water filter. Statistically, $E\left[T_{ic}u_{jic}\right] \neq 0$,

which leads to bias when β_1 is estimated using ordinary least squares.

Overcoming this identification problem requires an instrument that is correlated with T_{ic} but uncorrelated with u_{jic}. Both BDM and TIOLI provide such an instrument. In the case of BDM, this is the price draw; in the case of TIOLI, it is the offer price. We denote both as P_{ic}. In both cases, P_{ic} is random, so it is uncorrelated with u_{jic}, and because demand slopes down over our range of P_{ic}, it is correlated with T_{ic}. In a simple linear two-stage least squares (2SLS) framework, the first-stage equation is

$$T_{ic} = \gamma_0 + \gamma_1 P_{ic} + v_{ic}, \tag{5}$$

where P_{ic} is the BDM draw, and the predicted values $\hat{T}_{ic}$ are substituted into Equation 4 to obtain $\hat{\beta}_1^{IV}$.

$\hat{\beta}_1^{IV}$ estimates a local average treatment effect, where the complier group is those whose treatment status would change as a result of experimental variation in the offer price. Define $\beta_1(w)$, the average treatment effect for those with WTP $= w$, and $F_{\text{WTP}}(w)$, the CDF of WTP in the study population. The parameter estimated by instrumenting with a randomized price, β_1^{IV}, is a weighted average of these $\beta_1(w)$, where the weights depend both on $F_{\text{WTP}}(w)$, the distribution of WTP in the study population, and on the range of prices used in the randomization. [29]

Because BDM both reveals WTP and produces random variation in filter allocation at every level of WTP, it is possible to recover more information about $\beta_1(w)$. With a sufficiently large sample, it would be possible to estimate $\beta_1(w)$ at every elicited level of WTP. This is the distribution of marginal treatment effects discussed in the extensive literature on heterogeneous treatment effects from Heckman, Urzua and Vytlacil. The key advantage of BDM is that it allows us to observe the relevant selection characteristic rather than treating it as a latent variable to be estimated.[30] In practice, we conduct a set of kernel IV regressions, estimating Equations 4 and 5 in

[29] The set of prices in TIOLI and the range of price draws in BDM determine the complier populations. These prices, combined with their distribution and the distribution of WTP in the subject population, determine the weights for calculating the local average treatment effect for a particular experimental mechanism. See Imbens and Angrist (1994) for details on the calculation of these weights.

[30] See, for example, Heckman and Vytlacil (2001), Heckman and Vytlacil (2005) and Heckman et al. (2006). Given an instrument Z, the MTE at z, $\beta(z)$, is the effect on those who are indifferent between treatment and non-treatment when $Z = z$. Our kernel IV estimates exactly this parameter, since by definition those with WTP $= z$ are indifferent be-

the neighborhood of each level of WTP to obtain $\hat{\beta}^{KIV}(w)$ at a set of evaluation points W.

6.2 Application

We first present conventional IV estimates using the the BDM draw as an instrument for take-up among BDM subjects and the randomly-assigned TIOLI price as an instrument for take-up among the TIOLI subjects. These serve as reference points to demonstrate the advantages of using BDM to recover MTEs. We estimate

$$y_{jic} = \beta_0 + \beta_1 T_{ic} + x'_{ic}\beta_2 + u_{jic} \tag{6}$$

by linear two-stage least squares, where y_{jic} is the outcome of interest is an indicator for whether child j of subject i in compound c has had one or more cases of diarrhea in the previous two weeks, T_{ic} is a dummy for whether subject i purchased the filter, and x_{ic} is a vector of covariates. To instrument for the endogenous treatment variable, we estimate the first-stage equation

$$T_{ic} = \gamma_0 + \gamma_1 P_{ic} + x'_{ic}\gamma_2 + v_{ic}, \tag{7}$$

where P_{ic} is the TIOLI offer price for TIOLI subjects and the BDM draw for BDM subjects. Since P_{ic} is random, it is uncorrelated with u_{jic} and therefore it is a valid instrument for treatment.

Panel A of Table 4 presents results from this estimation for our short-term (one month) follow-up data. In columns (1) and (2), we use only the TIOLI observations; with raw 2SLS in column (1) and adding covariates in column (2); in columns (3) and (4), we use only the BDM observations; and in columns (5) and (6) we pool the TIOLI and BDM data. Between the two elicitation mechanisms, the estimates have the same sign and are of similar magnitude. In Table 4, Panel B we examine our long-term data, collected in a random sub-sample of half our villages roughly one year after the filter sale. After one year, there is no evidence that the filter was effective at reducing

tween treatment and non-treatment when the price is z. We are grateful to Sergio Urzua and Ed Vytlacil for discussions on this point.

child diarrhea in either the TIOLI or BDM sample. In fact, the IV point estimates are *positive.* The filter appears to have increased the likelihood of childhood diarrhea. While precisely identifying the mechanisms behind this result is beyond the scope of our data, we speculate that it could be driven by compensatory behavior on the part of respondents, as has been found with clean water interventions in other contexts (Bennett, 2012).

The usefulness of BDM becomes apparent when we use the kernel IV approach described above to estimate the relationship between treatment effects and WTP. Beneath the estimated local average treatment effects there is substantial heterogeneity. The outcome variable, as above, is an indicator for whether the child has had one or more cases of diarrhea in the previous two weeks. We estimate treatment effects $\hat{\beta}^{KIV}(w)$ for each GHS 0.1 step from GHS 1 to GHS 6, which correspond approximately to the 0.1 and 0.9 quantiles of WTP in the BDM sample. We use an Epanechnikov kernel and Silverman's rule of thumb to choose the bandwidth.

We present the results in Figure 3. In the top panel (Fig. 3a), we consider the effect at the short-term (one-month) followup survey. The null short-term effect in the population overall (Table 5, Panel A, Col. 3 and 4) is consistent across the distribution of WTP, with no group clearly benefiting.[31] In the bottom panel (Fig. 3b), we repeat this analysis using the one-year follow up data. Although standard 2SLS detected no average treatment effect in the sample (Table 5, Panel B, Col. 3 and 4), Figure 3b reveals important heterogeneity. Estimated treatment effects are negative at low levels of WTP, i.e., diarrhea increases. Treatment effects then increase with WTP over most of its distribution, leveling off at about GHS 3.5. Above GHS 5, point estimates again decrease, although this is not precisely estimated.

This pattern resembles that of the relationship between WTP and use (Fig. 2b), suggesting that effort (maintaining and using the filter) is an important determinant of impacts.[32] As shown in Figure 2b, low-WTP households used the filter less intensively. Regarding the observed negative

[31] Since the distribution of WTP is concentrated in the lower values (median 2.5), the effective sample size falls as WTP increases. However, the effect on precision is mitigated by variation in the strength of the instrument with respect to WTP. See the Supplementary Materials for sample sizes and Shea's partial R-squared statistics for each level of WTP at which we took a kernel estimate (Shea, 1997).

[32] See Chassang et al. (2012) for an extensive discussion of how effort may affect estimated treatment effects in randomized experiments and its implications for external validity.

treatment effect for those with a low willingness to pay, we speculate that drinking water may have become contaminated as a result of improper use. Consistent with Bennett (2012), it is also possible that low-WTP households may have been more likely to engage in compensatory behavior that more than offset the benefits from the filters.

As noted above, the estimated distribution of MTEs allows us to perform counterfactual pricing policy experiments. While we are hesitant to draw general conclusions, the pattern of increasing treatment effects across most of the WTP distribution suggests that higher prices would allocate the filter to those who would benefit most. In fact, because the estimated treatment effects are negative for those with low WTP, a price of about GHS 2.9 would effectively screen out those with negative treatment effects (on average). A price of approximately GHS 3.5 would maximize the average treatment effects among those purchasing the filter. Note that such prices still reflect a substantial subsidy, on the order of 85% of the cost of manufacturing and delivering the filter.

7 Conclusion

This paper demonstrates that BDM can be a useful tool to enhance the information obtained from randomized experiments. We use BDM to elicit a complete demand curve for household water filters in rural Ghana. With minor modifications to the BDM mechanism commonly used in the lab, most notably, guided practice rounds for unrelated products and confirmation checks after individuals state their valuation, the procedure can be readily understood. Even in an environment with extremely low literacy and numeracy, BDM produced sensible results. We then estimate the effects of price paid on use of the filters and estimate how use varies by WTP. Finally, we combine the precise information on WTP, random allocation of the filter conditional on WTP, and data from two follow-up surveys to estimate heterogeneous treatment effects of the filters by WTP.

From the standpoint of pricing policy, our BDM results suggest that small positive prices for the filter do not substantially decrease demand. As prices increase and demand starts to fall, those with the least benefit from the filter are effectively screened out of receiving it. However, our com-

parisons of BDM- and TIOLI-elicited WTP suggest exercising caution in interpreting the BDM results to simulate purchase behavior under TIOLI. In particular, we find that TIOLI-measured WTP is higher than that of BDM. While we are agnostic as to which mechanism provides more accurate simulation of purchase behavior in other contexts (e.g., in a marketplace), our results do suggest that optimal pricing policy may depend on the mechanisms through which sales are conducted.

We are encouraged by the potential to use BDM in a wide variety of field settings. As shown here, this can further enrich the ongoing policy debate regarding the pricing of preventative and curative health products. Moreover, recent work is demonstrating the value of detailed WTP measures in other contexts, such as labor markets (e.g., Guiteras and Jack, 2014), weather insurance Cole et al. (2014), and environmental conservation (e.g., Jack, 2013).

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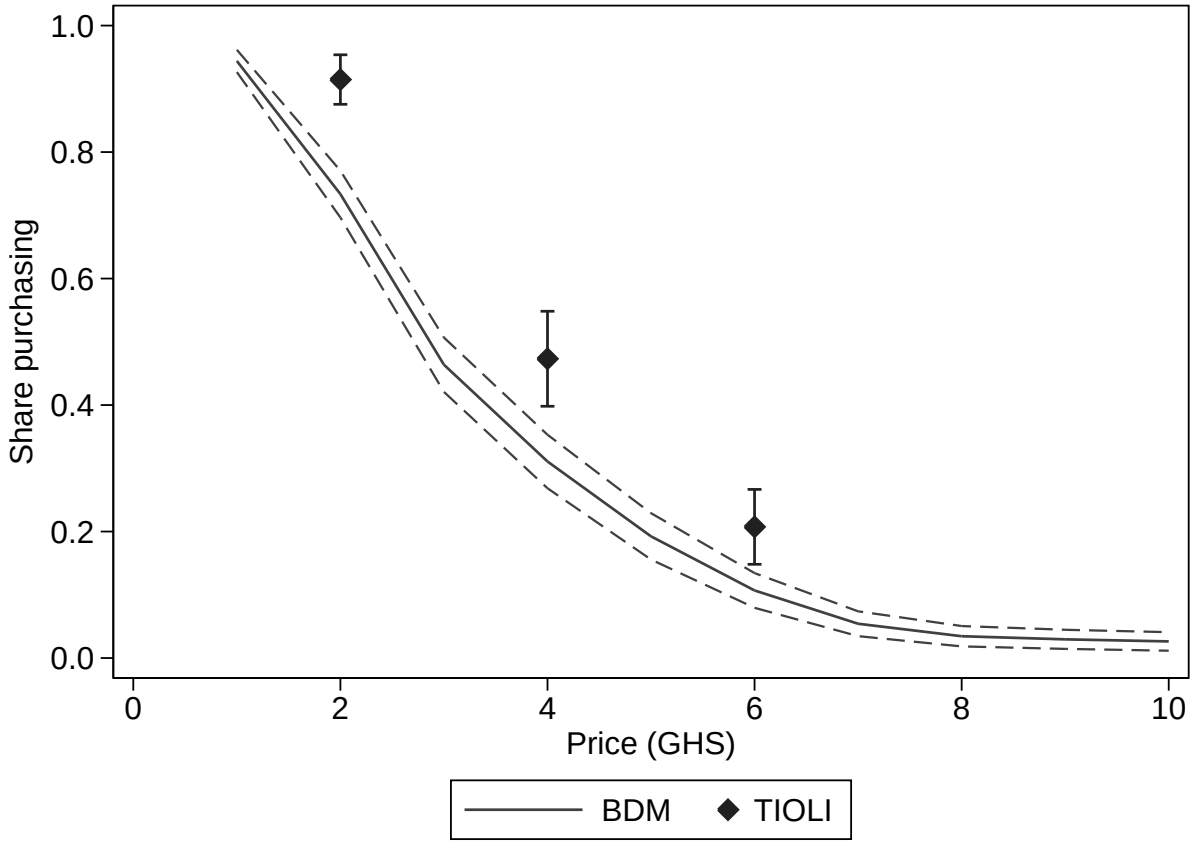
Figures and Tables

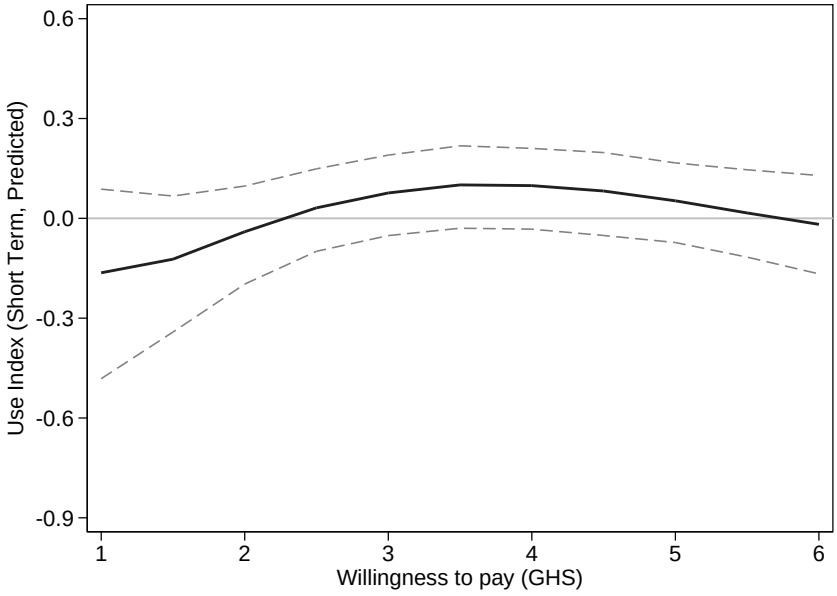
Figure 1: Inverse Demand



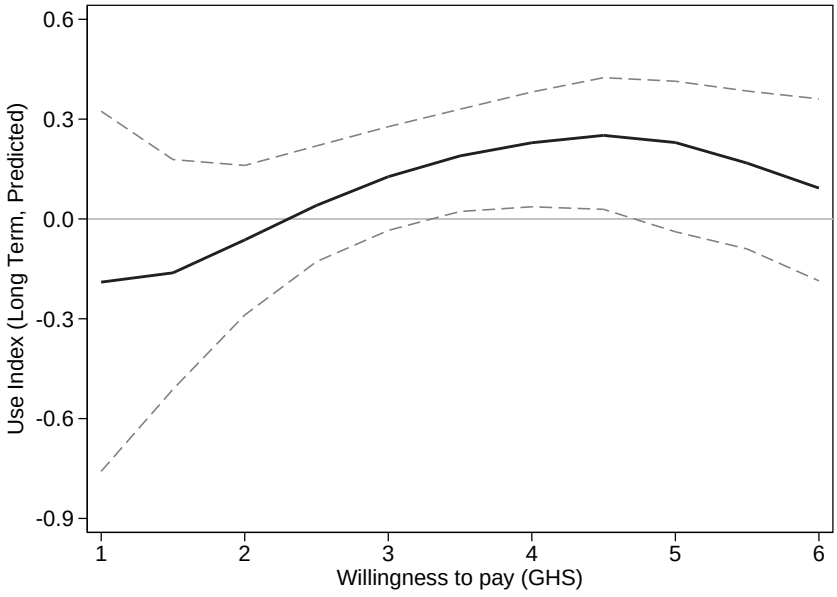
Notes: This figure plots the BDM demand curve, with a 90% confidence band, and take-it-or-leave-it (TIOLI) demand at three price points (2, 4 and 6 GHS), with 90% confidence intervals. The BDM demand curve indicates the share of respondents with a BDM filter bid greater than or equal to the indicated price. The TIOLI markers indicate the share of respondents who purchased the filter at the corresponding (random) price. Point-wise inference from logit regressions (at prices GHS 1, 2, . . . , 10 for BDM, 2, 4, 6 for TIOLI). Standard errors clustered at the compound (extended family) level. 608 BDM observations. 658 TIOLI observations, of which 246 at a price of 2, 224 at a price of 4, and 188 at a price of 6.

Figure 2: Relationship between Use and Willingness to Pay
BDM Purchasers with Children 0 to 5

(a) One-Month Follow-Up



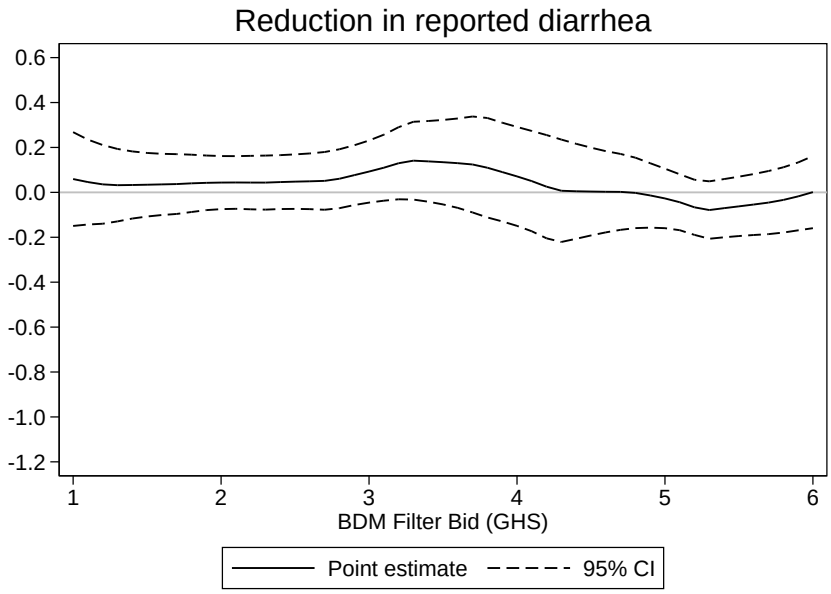
(b) One-Year Follow-Up



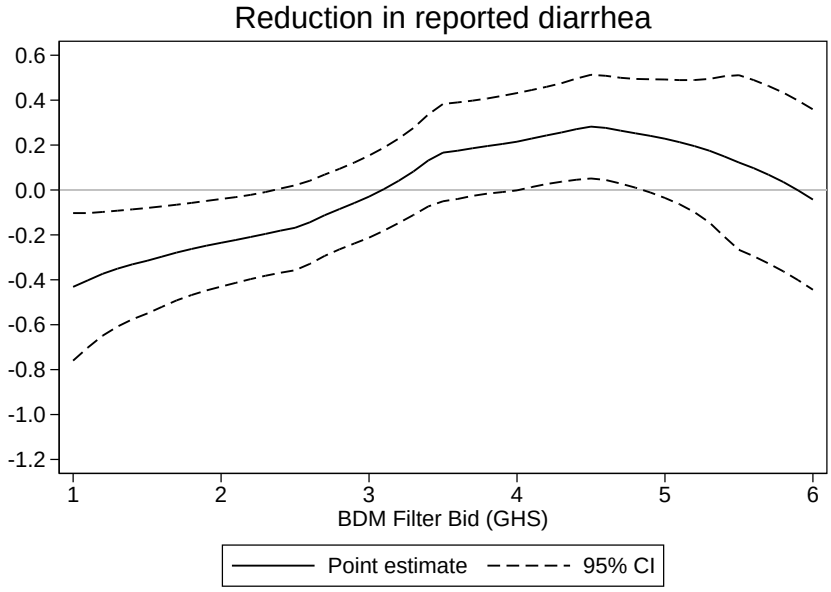
Notes: These figures show predicted values from a kernel regression (local polynomial of degree 1) of an index of use measures on the household's willingness to pay (WTP), as stated in the BDM sale. The index consists of indicators for whether the filter was observed in the compound, whether the safe storage container contained an appreciable amount of water (at or above the level of the spigot), and whether the ceramic pot contained water. These measures are standardized and averaged as in Kling, Liebman and Katz (2007). The sample consists of households that won a filter in the BDM sale and have one or more children age 0 to 5.

Figure 3: Kernel IV Estimates of Treatment Effects

(a) Short-term: One-Month Follow-Up



(b) Long-term: One-Year Follow-Up



Notes: These graphs present estimated treatment effects (reduction in diarrhea among children age 0 to 5) as a function of willingness to pay (WTP). Estimates are by linear two-stage least squares at WTP $= 1.0, 1.1, \ldots, 6.0$, weighting observations by their distance from the evaluation point using an Epanechnikov kernel. The endogenous treatment variable is an indicator for whether the household purchased a filter, and the exogenous instrument is the household's BDM draw. See Section 6.2 for details.

TABLE 1: SAMPLE COMPOSITION

	Mean[/a]			Diff[/b]		Regressions[/c]			
	Full Sample	BDM	TIOLI	BDM-TIOLI		BDM Draw		TIOLI Price	
	(1)	(2)	(3)	(4)		(5)		(6)	
Number of men in compound	3.072	2.839	3.287	-0.448	*	0.053		0.079	
	[2.018]	[1.773]	[2.200]	(0.257)		(0.116)		(0.079)	
Number of women in compound	4.284	3.939	4.602	-0.663		0.164	*	-0.081	*
	[2.930]	[2.089]	[3.506]	(0.426)		(0.097)		(0.041)	
Number of children age 0-5	1.302	1.387	1.224	0.163	*	0.051		-0.036	
in household	[1.282]	[1.304]	[1.258]	(0.084)		(0.129)		(0.047)	
Number of children age 6-17	1.134	1.067	1.196	-0.129	*	0.228		-0.000	
in household	[0.978]	[0.942]	[1.008]	(0.073)		(0.158)		(0.079)	
Number of children age 0-5 with	0.243	0.207	0.277	-0.069	**	-0.373		0.109	
diarrhea in past two weeks	[0.525]	[0.487]	[0.557]	(0.035)		(0.377)		(0.130)	
Number of children age 6-17 with	0.049	0.050	0.048	0.002		-0.485		0.461	*
diarrhea in past two weeks	[0.272]	[0.302]	[0.241]	(0.016)		(0.406)		(0.263)	
Respondent has ever attended	0.090	0.079	0.100	-0.021		0.001		-0.066	
school	[0.286]	[0.270]	[0.301]	(0.016)		(0.519)		(0.192)	
First principal component of	0.133	0.062	0.198	-0.136		-0.049		-0.006	
durables ownership	[1.555]	[1.512]	[1.592]	(0.125)		(0.092)		(0.054)	
All-year access to improved water	0.187	0.196	0.179	0.016		-0.152		0.121	
source	[0.390]	[0.397]	[0.384]	(0.038)		(0.382)		(0.249)	
Currently treats water	0.115	0.110	0.120	-0.010		0.472		0.048	
	[0.320]	[0.313]	[0.325]	(0.024)		(0.461)		(0.253)	
E. coli count, standardized	-0.052	-0.026	-0.076	0.050		-0.111		0.047	
	[0.949]	[1.012]	[0.887]	(0.089)		(0.164)		(0.119)	
Turbidity, standardized	-0.065	-0.099	-0.032	-0.068		-0.032		0.232	***
	[0.997]	[0.922]	[1.063]	(0.096)		(0.182)		(0.077)	
BDM bid						-0.090			
						(0.063)			
Number of observations	1266	608	658			608		658	
Number of cluster observations	552	273	279			273		279	

Notes: [/a] Columns 1, 2, and 3 display sample means in the full sample, BDM treatment, and TIOLI treatment, respectively. [/b] Column 4 displays the differences in means between the BDM and TIOLI treatments. [/c] Column 5 displays the results of a regression of BDM draw on the listed characteristics. Column 6 displays the results of a regression of TIOLI price on the listed characteristics. Missing values of independent variables in Columns 5 and 6 are set to 0, and dummy variables are included to indicate missing values. Standard deviations of variables appear in square brackets and standard errors, clustered by compound, appear in parentheses. * Denotes significance at the 10%-level, ** at the 5%-level, and *** at the 1%-level.

TABLE 2: CORRELATES OF WILLINGNESS TO PAY[/a]

	OLS	Probit	
	BDM-Estimated WTP[/b]	TIOLI Purchase[/c]	Diff.
	(1)	(2)	(3)
Number of men in compound	0.035	-0.144	0.179
	(0.096)	(0.088)	(0.131)
Number of women in compound	0.001	0.006	-0.005
	(0.071)	(0.052)	(0.088)
Number of children age 0-5	0.013	0.183 **	-0.170
	(0.065)	(0.080)	(0.104)
Number of children age 6-17	0.059	-0.070	0.130
	(0.107)	(0.097)	(0.145)
Number of children age 0-5 with	0.567 *	-0.268	0.834 **
diarrhea in past two weeks	(0.290)	(0.171)	(0.336)
Number of children age 6-17 with	-0.185	-0.648 *	0.463
diarrhea in past two weeks	(0.221)	(0.377)	(0.437)
Ever attended school	0.590	-0.484 **	1.074 **
	(0.410)	(0.238)	(0.475)
First principal component of	0.133 *	0.082	0.051
durables ownership	(0.074)	(0.075)	(0.105)
All-year access to improved water	-0.322	-0.206	-0.116
source	(0.256)	(0.271)	(0.373)
Currently treats water	0.573	0.219	0.354
	(0.367)	(0.278)	(0.460)
E. coli count, standardized	-0.122	0.134	-0.256
	(0.109)	(0.163)	(0.196)
Turbidity, standardized	-0.191 **	0.051	-0.242
	(0.084)	(0.134)	(0.158)
P-value: All coefficients = 0	0.0244	0.0047	0.0014
R-squared	0.053		
Number of Observations	608	658	1266

Notes: [/a] Standard errors, clustered at the compound (extended family) level in parentheses. * Denotes significance at the 10%-level, ** at the 5%-level, and *** at the 1%-level. [/b] Column (1) displays coefficients from a linear regression of directly reported willingness to pay (the BDM bid) on baseline characteristics. [/c] Column (2) reports probit estimates of purchase decisions. As discussed in Section 4, by restricting the coefficient on price to equal -1 in the probit estimation, the estimated coefficients can be interpretable in terms of willingness to pay. Missing values of independent variables are set to 0, and dummy variables are included to indicate missing values.

TABLE 3: CAUSAL EFFECT OF PRICES[/a]

	Filter Present and Undamaged [/b]	Storage Vessel Contains Water	Clay Pot Contains Water	Usage Index
	(1)	(2)	(3)	(4)
A. Short-term effects				
Draw	0.016	0.035	-0.004	0.040
	(0.018)	(0.021)	(0.024)	(0.038)
Mean Dependent Variable	0.877	0.754	0.729	-0.001
R-squared	0.017	0.013	0.007	0.011
Observations	236	236	236	236
B. One-year effects				
Draw	0.001	0.028	0.021	0.034
	(0.035)	(0.031)	(0.032)	(0.051)
Mean Dependent Variable	0.636	0.483	0.378	0.059
R-squared	0.005	0.029	0.010	0.008
Observations	143	143	143	143

Notes: [/a] The sample includes those subjects in the BDM treatment who purchased the filter, i.e., drew a price less than or equal to their bid. Each column presents the results of a separate regression of the dependent variable, listed in the column heading, on BDM draw and a cubic function of BDM bid. Standard errors, clustered at the compound (extended family) level in parentheses. * Denotes significance at the 10%-level, ** at the 5%-level, and *** at the 1%-level. [/b] See Section 5 for discussion of data. Usage index is the average of the normalized values of the three individual usage measures. Usage measures are observed by enumerator at indicated follow-up survey.

TABLE 4: SCREENING EFFECT OF PRICES[/a]

	Filter Present and Undamaged[/b]	Storage Vessel Contains Water	Clay Pot Contains Water	Usage Index
	(1)	(2)	(3)	(4)
A. Short-term effects				
Bid	-0.010	-0.008	-0.009	-0.022
	(0.010)	(0.012)	(0.013)	(0.021)
Mean Dependent Variable	0.877	0.754	0.729	-0.001
R-squared	0.006	0.002	0.003	0.006
Observations	236	236	236	236
B. One-year effects				
Bid	0.013	0.027 *	-0.013	0.018
	(0.014)	(0.014)	(0.012)	(0.021)
Mean Dependent Variable	0.636	0.483	0.378	0.059
R-squared	0.005	0.023	0.005	0.005
Observations	143	143	143	143

Notes: [/a] The sample includes those subjects in the BDM treatment who purchased the filter, i.e., drew a price less than or equal to their bid. Each column presents the results of a separate regression of the dependent variable, listed in the column heading, on the willingness to pay, i.e. the subject's bid in BDM. Standard errors, clustered at the compound (extended family) level in parentheses. * Denotes significance at the 10%-level, ** at the 5%-level, and *** at the 1%-level. [/b] See Section 5 for discussion of data. Usage index is the average of the normalized values of the three individual usage measures. Usage measures are observed by enumerator at indicated follow-up survey.

TABLE 5: INSTRUMENTAL VARIABLES ESTIMATES OF TREATMENT EFFECTS[/a]

Dependent variable: Child aged 0-5 has had diarrhea over previous two weeks

	TIOLI Subjects		BDM Subjects		Combined all subjects	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Short-term effects						
Filter Purchase	-0.100 *	-0.110 **	-0.049	-0.057	-0.072 **	-0.079 **
	(0.054)	(0.051)	(0.050)	(0.044)	(0.035)	(0.034)
Controls[/b]	NO	YES	NO	YES	NO	YES
Village FEs	NO	YES	NO	YES	NO	YES
Mean Dependent Variable	0.149	0.149	0.142	0.142	0.145	0.145
R-squared		0.068		0.102		0.054
Observations	665	665	579	579	1244	1244
B. One-year effects						
Filter Purchase	0.148	0.226 **	0.090	0.109	0.105	0.130 *
	(0.099)	(0.110)	(0.089)	(0.090)	(0.067)	(0.068)
Controls	NO	YES	NO	YES	NO	YES
Village FEs	NO	YES	NO	YES	NO	YES
Mean Dependent Variable	0.215	0.215	0.262	0.262	0.241	0.241
R-squared	.	0.093	0.006	0.118	0.003	0.067
Observations	266	266	273	273	539	539

Notes: [/a] Each column displays the results of a 2SLS regression of child diarrhea status at the child level on filter purchase, where filter purchase is instrumented for by random BDM draw for BDM subjects and by randomly assigned TIOLI price for TIOLI subjects. Standard errors, clustered at the compound (extended family) level in parentheses. * Denotes significance at the 10%-level, ** at the 5%-level, and *** at the 1%-level. [/b] Controls include all variables (other than BDM draw) listed in Table 1. Missing values of independent variables are set to 0, and dummy variables are included to indicate missing values.

A Appendix

Figure A1: The *Kosim* filter

B BDM Script

Section numbers refer to survey instrument. For full text of all sales treatments, see the Supplemental Materials.

J. REGULAR_BDM

READ EXACTLY FROM SCRIPT. DO NOT SAY ANYTHING THAT IS NOT IN SCRIPT.

READ:

- We would like to sell you a filter but the price is not yet fixed. It will be determined by chance in a game we are about to play.

- You will not have to spend any more for the filter than you really want to.

- You may even be able to buy it for less.

Here is how the promotion works:

- I will ask you to tell me the maximum price (***dan kuli***) you are willing to pay (***ka a ni sagi dali***) for the *Kosim* filter (koterigu di mali lokorigu).

- In this cup, I have many different balls with different numbers on them.

- The numbers represent prices for the filter.

- Then I will ask you to pick a ball from the cup, and we will look at the price together.

- If the number you pick is less than or equal to your bid, you will buy (***ani too dali***) the filter and you will pay the price you pick from the cup.

- If the number you pick is greater than your bid, then you cannot buy the filter.

- You will only have one chance to play for the filter.

- You cannot change your bid after you draw from the cup.

- You must state a price that you are actually able to pay now.

- We will practice in one moment, but for now, do you have any questions?

Answer any questions respondent has.

J.1 REGULAR_BDM PRACTICE

REMEMBER: Get respondent to state HIGHEST price they are WILLING AND ABLE to pay right now.

NOTE: Refer to p.23 for correct Dagbani translation of Cedi amounts.

- Before we play for the filter, let's practice the game. We'll play the same game, but instead of playing for the filter, we will play for this bar of soap. ***Show respondent soap.***

1) What is the maximum amount (dan kuli) that you are willing to pay for this soap? **[*Respondent states price X*]**

2) Now, if you pick a number that is less than or equal to X, you will buy the soap at the price you pick. If you pick a number greater than X, you will not be able to purchase the soap, even if you are willing to pay the greater number. You cannot change your bid after you pick a price. Do you understand?

3) Please, tell me - if you pick [X+5 peswas] now, what happens? ***If respondent does not give correct answer, explain the rules again and then ask question again.***

4) And if you pick [X-5 peswas] now, what happens? ***If respondent does not give correct answer, explain the rules again and then ask question again.***

5) If you draw [X+5], will you want to purchase the soap for [X+5]?
IF YES: → **5)**
IF NO: → **6)**

6) Do you want to change your bid to [X+5]?
IF YES: OK, your new bid is [X+5]. → **2) [*use* X+5 *as new* X]**
IF NO: → **6)**

7) So, is X truly the most you would want to pay?
IF YES: → **7)**
IF NO: → **1)**

8) If you pick X, you must be able to pay X. Are you able to pay X now?
IF YES: → **J.1.1**
IF NO: What is the maximum price you are willing **and able** to pay now? → **2) [*use new X*]**

→ ***Record respondent's Final Bid*** (J.1.1, page 29)

9) Could you please fetch the amount you have stated you are willing to pay and show it to me?
Wait for respondent to fetch money and check to see she has enough funds for Final Bid.

10) Now you will pick a price from the cup. If you pick X or less, you will buy the soap at the price you pick. If you pick more than X, you will not be able to buy the soap. Are you ready to pick a ball?

Mix balls in cup, hold cup above eye level of respondent and have her pick a ball without looking.

11) Now you can draw a ball from the cup. ***Let respondent draw ball. Together, look at the ball and read the price picked.*** **[*Drawn price is Y*]**

→ ***Record Drawn Price*** (J.1.2, page 29)

12) Let us look at the ball together.

→ ***Record if Drawn Price is lower/equal to or higher than Final Bid Survey*** (J.1.3, page 29)

a. **[*If Y* <= *X*]:** The price is Y which is [less than/equal to] the amount you said you would be willing and able to pay for this soap. You can now buy the item at this price.

   → ***Exchange payment for soap.***

b. **[*If Y* > *X*]:** The price is Y, which is greater than the amount you said you would be willing to spend. You cannot purchase the soap.

13) Do you have any questions about the game?

Address any questions or concerns respondent has. Make sure she understands rules of game.

J.2 REGULAR_BDM FILTER SALE

REMEMBER: Get respondent to state HIGHEST price they are WILLING AND ABLE to pay right now.

NOTE: Refer to p.23 for correct Dagbani translation of Cedi amounts.

Read:

- Now you will play to buy the filter
- Recall the community meeting on [day of community meeting]
- Have you thought about how much you are willing to pay for the filter?
- Do you have the funds available now?

Let's begin:

1) What is the maximum amount (dan kuli) that you are willing to pay for this filter? **[*Respondent states price X*]**

2) Now, if you pick a number that is less than or equal to X, you will buy the soap at the price you pick. If you pick a number greater than X, you will not be able to purchase the soap, even if you are willing to pay the greater number. You cannot change your bid after you pick a price. Do you understand?

3) Please, tell me - if you pick [X+1 cedis] now, what happens? ***If respondent does not give correct answer, explain the rules again and then ask question again.***

4) And if you pick [X-1 cedis] now, what happens? ***If respondent does not give correct answer, explain the rules again and then ask question again.***

5) If you draw [X+1], will you want to purchase the filter for [X+1]?

IF YES: → **5)**
IF NO: → **6)**

6) Do you want to change your bid to [X+1]?

IF YES: OK, your new bid is [X+1]. → **2) [*use* X+1 *as new* X]**
IF NO: → **6)**

7) So, is X truly the most you would want to pay?

IF YES: → **7)**
IF NO: → **1)**

8) If you pick X, you must be able to pay X. Are you able to pay X now?

IF YES: → **J.2.1**
IF NO: What is the maximum price you are willing **and able** to pay now?
→ **2) [*use new X*]**

→ ***Record respondent's Final Bid*** (J.2.1, page 29)

9) Could you please fetch the amount you have stated you are willing to pay and show it to me?
Wait for respondent to fetch money and check to see she has enough funds for Final Bid.

10) Now you will pick a price from the cup. If you pick X or less, you will buy the filter at the price you pick. If you pick more than X, you will not be able to buy the filter. Are you ready to pick a ball?

Mix balls in cup, hold cup above eye level of respondent and have her pick a ball without looking.

11) Now you can draw a ball from the cup. ***Let respondent draw ball. Together, look at the ball and read the price picked.*** **[*Drawn price is Y*]**

→ ***Record Drawn Price*** (J.2.2, page 29)

12) Let us look at the ball together.

→ ***Record if Drawn Price is lower/equal to or higher than Final Bid*** (J.2.3, page 29)

a. **[*If Y* <= *X*]:** The price is Y which is [less than/equal to] the amount you said you would be willing and able to pay for this filter. You can now buy the filter at this price.

   →***Receive payment for filter. Record filter tracking code on survey*** (I.2.5, page 29). ***Record filter tracking code on receipt and give it to respondent. Inform her of where and when she can pick up the filter.***

b. **[*If Y* > *X*]:** The price is Y, which is greater than the amount you said you would be willing to spend. You cannot purchase the filter.

→***Go to Household Survey question*** J.24, page 29