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The Price of Purity: Willingness to Pay for Air and Water Purification Technologies in Rajasthan, India

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Abstract
Diarrheal illnesses and acute respiratory infections are among the top causes for premature death and disability across the developing world, and adoption of various technologies for avoiding these illnesses remains extremely low. We exploit data from a unique contingent valuation experiment to consider whether households in rural Rajasthan are unwilling to make investments in "domain-specific" environmental health technologies when faced with health risks in multiple domains. Results indicate that demand for water-related risk reductions is higher on average than demand for air-related risk reduction. In addition, households' private health benefits from mitigating diarrheal (respiratory) disease risks are higher (no different) when community-level air pollution risks, rather than community-level water pollution risks, have previously been mitigated. This asymmetric response cannot fully be explained by survey order effects or embedding, but rather suggests that that the broader health environment and the salience of particular risks may be important in households' decision to adopt environmental health technologies.

Keywords Household air pollution · Diarrheal diseases · Technology adoption · Contingent valuation

JEL Classification Q51 · Q53 · Q56

1 Introduction

Diarrheal illnesses and acute respiratory infections continue to rank among the top causes for premature death and disability across South Asia (Institute for Health Metrics and Evaluation 2013). In India alone, it is estimated that diarrheal and respiratory illnesses are responsible

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for up to 6% of deaths (World Health Organization 2015). Children under five are particularly vulnerable to these infections, and there has long been speculation about the incidence of dual or sequential infections due to children's lesser immune function and the high incidence of malnutrition in at-risk communities (Guerrant et al. 2012; Walker et al. 2013).

Two important facts about environmental health conditions such as diarrhea and many respiratory illnesses are, first, that these conditions are preventable and, second, that many of the technologies that facilitate prevention are low-cost, readily available, and easy to use. For reducing the risk of diarrheal illnesses, point-of-use (POU) technologies such as boiling, liquid hypochlorite solution, disinfectant powders, solar disinfection, and various types of filtration devices are effective in combatting water contamination at the household level (Clasen et al. 2007; Fewtrell et al. 2005).[1] Meanwhile, household air pollution can be reduced through the use of improved cookstoves (ICS) or modern fuels (Anenberg et al. 2013). When compared with traditional biomass stoves, more efficient cooking technologies not only cut down on harmful emissions, they also decrease cooking times and use less fuel (Bensch et al. 2015; Bensch and Peters 2015; Brooks et al. 2016).

Despite these positive expected impacts, adoption and sustained use of environmental health technologies remains hard to achieve in poor, rural, and vulnerable communities (Jeuland et al. 2015d; Lewis and Pattanayak 2012; Whittington et al. 2012). Lack of demand among the rural poor is especially problematic as such households often face a greater burden from preventable illnesses (Braveman 2006).

At the same time, it is undeniable that poor households face myriad competing demands for limited resources (Banerjee and Duflo 2007). These competing demands may be especially salient in the health domain if households are unsure how to prioritize reductions in risks of different illnesses (Dow et al. 1999). Furthermore, the inability to save money or pay for the full up front cost of a technology may make households less likely to adopt preventative health products (Dupas and Robinson 2013). Complicating matters further, households typically consider non-health motives in deciding to adopt and use new technologies such as ICS or water treatment (Pattanayak and Pfaff 2009; Poulos et al. 2012; Thurber et al. 2013). Various factors such as convenience of use and changes in the taste of water or food can also make uptake of these technologies difficult to sustain (Bhojvaid et al. 2014; Jeuland et al. 2015c). As a result of these and other challenges, it is not uncommon for the use of various health technologies (e.g., bed nets, ICS, or water treatment products) to diminish over time due to broken equipment, lack of replacement of consumables, or simple reversion back to former behaviors once promotion interventions have ended (Hensher et al. 2005; Luoto et al. 2011).

This existing literature clearly illustrates the myriad significant barriers to adoption of technologies for improving environmental health. Achieving greater prevention behavior thus presents important logistical challenges, and suggests a need for gaining a thorough understanding of consumer preferences for different solutions, prior to implementing efforts to stimulate demand. Needless to say, understanding what drives demand for preventive technologies is imperative to ensure future success in implementation, marketing, and behavior change or educational campaigns, and for improving health outcomes.

[1] POU water treatment technologies have gained prominence largely due to the continuing high reliance in many rural and low-income settings on community sources located outside the home. Water obtained from such sources varies in quality, and there is strong empirical evidence that water safety can be compromised between the time of collection and the time of consumption due to transport and storage, even when source water quality is fairly good. For example, Gasana et al. (2002) find that water tested at various source points indicated no risk to consumers, but that contamination levels were significantly higher at the point of use; there is similar evidence from other settings (Kremer et al. 2011; Rufener et al. 2010). In addition, investments in water infrastructure may also crowd out preexisting private prevention behavior, offsetting expected health benefits (Bennett 2012; Jessoe 2013; Jeuland et al. 2015b).

User preferences can be studied *ex ante* using a number of different approaches. Discrete choice experiments, for example, can be used to study how potential beneficiaries prioritize specific features of environmental health products (Jeuland et al. 2015a; Poulos et al. 2012). In this paper, however, we are not particularly interested in describing the demand for specific preventive technologies, which is already the subject of a substantial literature that includes, among other papers, several of those cited above. Instead, our objective is to better understand household beliefs with respect to competing risks.

Specifically, we study the relative perception of reduced health risks that would stem from hypothetical air and water quality improvements. To achieve this objective, we use the contingent valuation method (CVM), which is a common technique for determining the value of goods that are not bought and sold in ordinary markets (Hanemann 1994). This approach allows for estimation of a household demand curve for hypothetical improvements by randomizing prices across survey respondents and observing respondent willingness to pay at those different prices. While the CVM was initially introduced for valuing non-market environmental commodities, it is increasingly common in economic evaluations of healthcare and health improvement (Kartman et al. 1996; Lucas et al. 2007; Martín-Fernández et al. 2013). Previous work has stressed the importance of careful CVM study design and implementation, and critiques of the method are widespread (Carson 2000; Whittington 2002). Despite the well-known limitations of the CVM, it is appropriate for use in our study because it allows us to focus respondents' attention on specific changes in the risks of two types of illnesses—respiratory infections and diarrheal disease. Given that the typical implementation strategy (e.g., followed by government or NGOs) is to focus on interventions that target isolated problems, the CVM offers greater flexibility for studying the problem of complementarities in different types of health risk reductions.

Our study fits into a relatively broad literature that considers the willingness to pay (WTP) for environmental health improvements in low-income countries. Much of this prior literature is specific to measuring demand for household water treatment (Null et al. 2012; Orgill et al. 2013; Orgill-Meyer et al. 2018; Poulos et al. 2012; Van Houtven et al. 2017), with comparatively fewer studies—mostly discrete choice experiments—focusing on demand for technologies that reduce household air pollution (Jeuland et al. 2015a; Mobarak et al. 2012; van der Kroon et al. 2014). To the best of our knowledge, no previous study has explored WTP for these technologies in tandem, although public health researchers have considered the impacts of combined ICS and water treatment interventions (Rosa et al. 2014). Given that there is significant overlap in the burdens of disease due to diarrheal and respiratory illnesses in low-income contexts (as shown in Fig. 1), this is a prominent gap in our knowledge regarding the benefits of potentially lifesaving health products for the world's poor. In addition, our study design explores the extent to which the relative sequencing of the air and water quality solutions impacts stated WTP, which may shed light on the consistency of survey order effects or perceived complementarities across such hypothetical interventions.

This paper proceeds as follows. Section 2 presents a background on the drivers of demand for technologies that reduced water- and household-air-pollution-related risks, and discusses results from the existing literature on "order effects" in CVM studies, which are relevant for our work because we present respondents with offers for multiple hypothetical improvements in sequence. Section 3 outlines our study design and theoretical framework. Section 4 provides an overview of our sample, and presents key results. Section 5 presents the willingness to pay estimates obtained from these results. Section 6 features a discussion of our results, and Sect. 7 concludes.

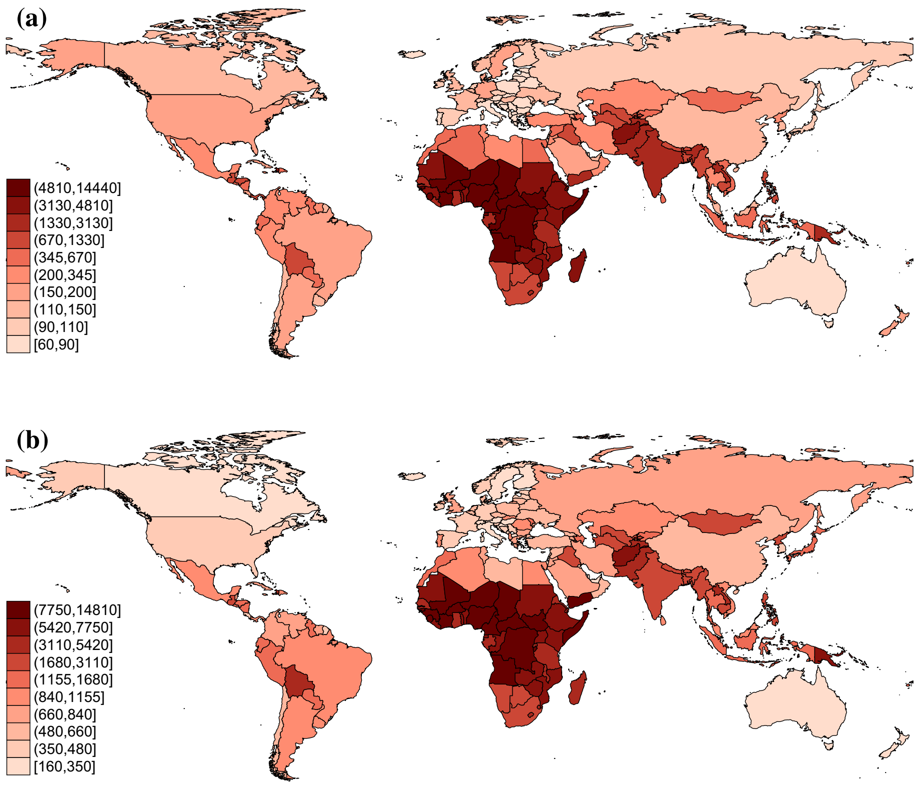

Fig. 1 Global burden of disease due to diarrhea and respiratory infections **a** Diarrheal diseases, Disability Adjusted Life Years (DALYs) per 100,000 and **b** Respiratory infections, Disability Adjusted Life Years (DALYs) per 100,000. Burden of disease data obtained from the World Health Organization (2014)

2 Background

Many researchers have examined the set of socioeconomic and demographic drivers of demand for technologies that reduce water- and air-related disease risks. Lewis and Pattanayak (2012) synthesize the existing empirical evidence on determinants of ICS and clean-fuel adoption and find a "systematic and theoretically consistent relationship between adoption of clean energy products and socioeconomic status (including income, education, and social marginalization) and urban location." These findings are largely consistent with the correlates identified by Rehfuess et al. (2013), who also include qualitative analyses and case studies in their review. Others have studied the important role played by household preferences (Ouedraogo 2006); social networks (Miller and Mobarak 2015); use-based incentives (Usmani et al. 2017); and the relative availability and affordability of substitute technologies or fuels (Beyene and Koch 2013).

Demand studies that focus on POU water treatment technologies highlight a similar set of factors. Despite their low cost and efficacy, poverty and lack of education pose significant barriers to adoption (Freeman et al. 2009; Hunter 2009). Subsidies can be effective at increasing adoption (Null et al. 2012), though the role of positive prices in screening out those most likely to actually use POU technology remains a matter of some debate (Ashraf et al. 2010). Experimental evidence suggests that a lack of knowledge about contamination risks may also suppress demand, particularly among households with low socio-economic status (Brown et al. 2016; Hamoudi et al. 2012; Orgill et al. 2013). In addition, there are signs that additional unrecognized barriers exist beyond "traditional" constraints related to income and information (Luoto et al. 2011). In particular, preferences for POU technologies have been found to be heterogeneous, and distaste or inconvenience often appears to discourage adoption (Jeuland et al. 2015c). Research also points to the importance of psycho-social (behavior change) interventions that activate households' awareness of the benefits of POU technologies in new and effective ways (Blanton et al. 2010; Boisson et al. 2010).

As mentioned above, although the prior literature has analyzed demand for each of household water treatment and household air pollution reduction technologies separately, we are not aware of any study that has looked at WTP for the two sets of technologies in tandem. An important challenge in conducting such a study of two technologies—which we address by randomizing the order in which the two technologies are presented to each respondent—arises from the fact that stated preference estimates have been found to be sensitive to order effects, whereby the sequencing of valuation questions affects the propensity to respond affirmatively to a given price offer (Halvorsen 1996). For instance, Samples and Hollyer (1990) find that survey respondents' willingness to pay to preserve seals from extinction is greatly affected by whether it is elicited before or after that for whales. Similarly, Powe and Bateman (2003) investigate the willingness of visitors to pay to prevent saline flooding in a wetland area in eastern England; they find that estimated WTP for a smaller component of the program is significantly higher if it is elicited before that for the larger component. While CVM surveys that elicit WTP for multiple projects or policies appear to yield lower estimates for items further down in the sequence (Hoehn and Loomis 1993), this is not always so (Clark and Friesen 2008). A variety of explanations have been advanced for the presence of CVM order effects, including strategic misrepresentation of WTP by respondents (Clark and Friesen 2008); respondents' desire to purchase "moral satisfaction" (Kahneman and Knetsch 1992); and the extent to which the goods being valued are substitutes (Carson et al. 1993). More recent work has also found that adjusting the way stated preference surveys are executed can reduce WTP estimates (Cook et al. 2011; Longo et al. 2015).

3 Methodology

3.1 Sample Selection and Study Design

Our data come from a baseline household survey conducted in collaboration with a local non-governmental organization between August and October 2013 in the Udaipur district of Rajasthan, India. The final sample included 900 households living in sixty villages; fifteen households were randomly selected to participate in each village, using a field-based counting method. In our analysis, results from 38 households were dropped due to incomplete surveys.

The household survey instrument included questions on household composition, demographics, and socioeconomic status; respiratory illness and diarrheal disease prevalence; fuel and water sources; water treatment, storage, and hygiene behaviors; WTP for reduced risk of respiratory or diarrheal illness; as well as detailed perceptions of environmental risks including those associated with poor air and drinking water quality. Table 1 presents a description of some of the key variables collected through the survey, while Table 2 presents descriptive statistics for the 862 households included in our final analytical sample.

As noted before, the demand for preventative health products incorporates dimensions such as convenience of use, reliability, aesthetics, and cost. The purpose of the CVM exercise

Table 1 Descriptions of key variables

VARIABLE	DESCRIPTION
ACCEPTWATER	= 1 if accepted offer for water purifier
ACCEPTAIR	= 1 if accepted offer for air purifier
PRICE	Price offer (current US dollars)
WATERFIRST	= 1 if WTP offer option "A" (community ARI scenario + option to buy water filter first)
PRICE × WATERFIRST	PRICE × WATERFIRST
HHSIZE	Household size
CHILD5	Number of children under five
FEMALEHEAD	= 1 if female-headed household
CASTE	= 1 if classified as SC/ST/NT/OBC ("lower caste")
HINDU	= 1 if Hindu
EDUCATION	Average minimum years of education (adults in household)
EDUCATIONFEMALE	Average minimum years of education (females in household)
EDUCATIONMALE	Average minimum years of education (males in household)
ROOMS	Number of rooms
FARMER	= 1 if household head employed in agriculture
POVLINE	= 1 if below poverty line
ELECTRICITY	= 1if access to electricity "all the time" or "sometimes"
HEARDICS	= 1 if heard of improved cookstoves (ICS)
NEGSTOVE	= 1 if heard of negative impacts of cooking smoke
EXPENDITURE	Monthly expenditure (current US dollars)
VILLCLEAN	= 1 if cleanliness of village "very clean" or "clean"
ARIFATAL	= 1 if respiratory illness indicated as "most dangerous" (fatal)
REGULARICS	= 1 if ICS used at least "3–4 times per week"
CLEANFUEL	= 1 if clean fuel used (not necessarily exclusively)
IMPROVEDWATER	= 1 if main drinking water source is "improved" (WHO definition)
UNSAFEWATER	= 1 if unsafe method of pouring drinking water demonstrated
HEARDWASH	= 1 if received WASH public health message in the past
WATERSAFETY	Drinking water safety perception (10 = completely safe; 0 = completely unsafe)
SMOKESAFETY	Stove smoke safety perception (10 = completely safe; 0 = completely unsafe)
DIARRPREVENT	= 1 if believes diarrhea can be prevented
COOKTIME	Total time spent cooking per day (hours)
COLLTIME	Total time spent collecting non-clean fuels per week (hours)
WATERCOLL	Total time spent collecting water per week (hours)
TOTALCOUGH	Number of household members who have suffered from cough/cold in the past two weeks
COUGHPAY	Total amount spent to treat most recent bout of all members' cough/cold (current US dollars)
TOTALDIARR	Total household days lost to most recent diarrheal episode (caring for someone or sick with diarrhea)

Table 1 continued

VARIABLE	DESCRIPTION
DIARRPAY	Total amount spent to treat most recent bout of all members' diarrheal illness (current US dollars)
CHILDDIARR	= 1 if any incidence of childhood diarrhea in household in the past two weeks
TOTALMALARIA	= 1 if any incidence of malaria in the past one year
HHTB	= 1 if any incidence of TB in the past

Table 2 Descriptive statistics

	MEAN	MEDIAN	SD	MIN	MAX
ACCEPTWATER	0.51	1	0.50	0	1
ACCEPTAIR	0.48	0	0.50	0	1
OPTION	0.49	0	0.50	0	1
PRICE	18.9	16.3	14.7	4.88	40.7
HHSIZE	5.63	6	2.00	1	15
CHILD5	0.43	0	0.66	0	4
FEMALEHEAD	0.033	0	0.18	0	1
CASTE	0.93	1	0.25	0	1
HINDU	1.00	1	0.034	0	1
EDUCATION	2.92	3	2.73	0	12
EDUCATIONMALE	4.09	3.50	3.76	0	21
EDUCATIONFEMALE	1.56	0	2.72	0	12
ROOMS	5.07	5	1.34	1	10
FARMER	0.53	1	0.50	0	1
POVLINE	0.78	1	0.42	0	1
ELECTRICITY	0.63	1	0.48	0	1
HEARDICS	0.59	1	0.49	0	1
NEGSTOVE	0.98	1	0.15	0	1
EXPENDITURE	99.1	87.8	59.6	17.9	887.8
VILLCLEAN	0.46	0	0.50	0	1
ARIFATAL	0.064	0	0.25	0	1
REGULARICS	0.068	0	0.25	0	1
CLEANFUEL	0.84	1	0.37	0	1
IMPROVEDWATER	0.56	1	0.50	0	1
UNSAFEWATER	0.71	1	0.46	0	1
HEARDWASH	0.99	1	0.084	0	1
WATERSAFETY	6.45	6	1.94	0	10
SMOKESAFETY	4.57	5	1.88	0	10
DIARRPREVENT	0.98	1	0.15	0	1
COOKTIME	3.25	3	1.79	0	33
COLLTIME	15.0	10	13.4	0	105.5
WATERCOLL	5.28	4.67	3.99	0	25.1

Table 2 continued

	MEAN	MEDIAN	SD	MIN	MAX
TOTALCOUGH	1.52	1	1.40	0	12
COUGHPAY	8.74	3.25	22.8	0	487.8
TOTALDIARR	2.40	0	5.42	0	53
DIARRPAY	4.44	0	15.0	0	308.9
CHILDDIARR	0.065	0	0.25	0	1
TOTALMALARIA	0.72	1	0.45	0	1
HHTB	0.022	0	0.15	0	1
Observations	855				

carried out in the survey was to measure WTP for diarrheal risk and respiratory risk reductions that would not be contaminated by these other features. As such, respondents were asked to imagine a hypothetical water purification technology and a hypothetical air purification technology that was costly but that would not affect other features of their drinking water or air supply.

3.2 The Contingent Valuation Experiment

Prior to survey administration, households were randomly assigned to two different option groups for the CVM scenario (i.e., 450 households each received an “Air framing” [Option A] or a “Water framing” [Option B]). For those assigned to Option A, the CVM scenario first asked households to imagine that an air quality program had been implemented in their community that would cost them a nominal amount of INR 50 (approximately $0.80 at the time) per year; knowing this information, they were then asked if they would also pay a randomly assigned annual price (ranging from INR 300 to INR 2500) to acquire and use a private household-level water purification device that would reduce the risk of diarrhea. For households assigned to Option B, the scenario was inverted: respondents were first asked to imagine a community-level water improvement program that had cost them INR 50 per year, and were then asked if they would also pay a randomly assigned price for a private household-level air purification device that would reduce the risk of respiratory illness.

In both the air (Option A) and water (Option B) frames, following responses to this first WTP question for the private improvement that would reduce the other disease, respondents were then asked a second WTP question about the private device that would reduce the risk of the other illness (a household-level air purifier in Option A, and a water purifier in Option B), which would further reduce risks that had already been reduced by the community-level intervention in that frame. In this second WTP question, the same randomly assigned price given for the first private device that targeted the other disease was again used for each household. The motivation for including this second question was to test for order effects or changes in the marginal value of additional risk reductions. Each of these could lead to systematic differences in the WTP for a purification device depending on whether it was offered first or second, and could shed light on perceived complementarities in disease risk reductions. Figure 2 provides a visual overview of our CVM experiment scenarios and ordering. The full scenario script and sample visuals that were used to illustrate the risk reduction concepts to respondents are included in Appendix A.

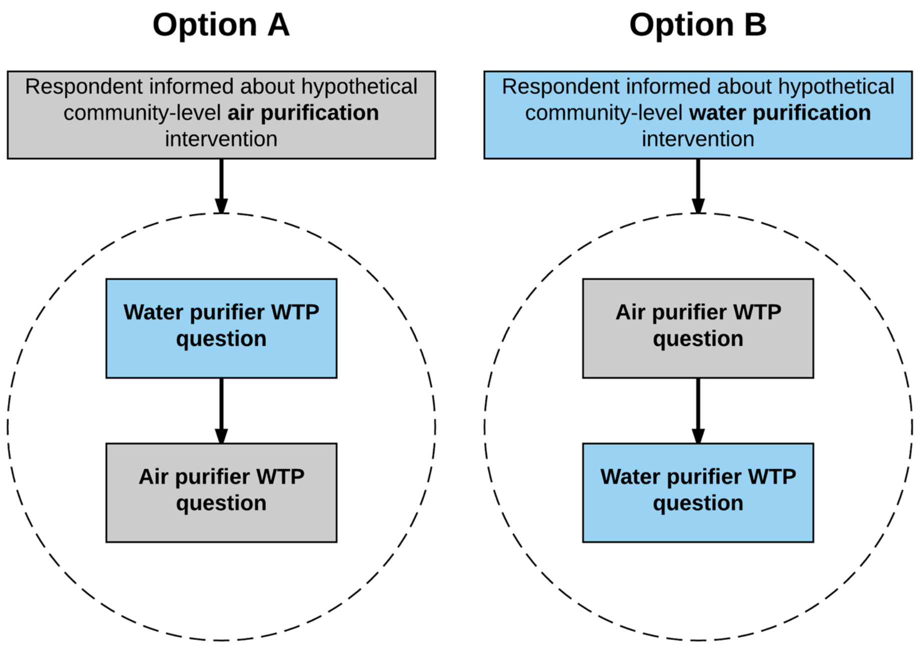

Fig. 2 Overview of contingent valuation experiment scenarios and ordering. Survey respondents were randomly assigned to one of the two outlined options

3.3 Theoretical Framework and Model Specification

Estimating separate univariate probit regressions for the decisions to accept the air and water purifier offers would ignore any overlap in unobserved characteristics that impact both purchase decisions (Greene 2011). We, thus, employ a bivariate probit regression approach to more consistently consider the association between household-level characteristics and demand. Explanatory variables for WTP were chosen based on findings from previous work that speaks to the demand for preventive health improvements (Lucas et al. 2007). For instance, households with young children—who are especially susceptible to diarrheal and respiratory illnesses—or those that believe these diseases can be prevented may be more willing to pay for health improvements. On the other hand, households that perceive their current environmental quality to be safe, or that do not believe that these illnesses can be prevented, may be less willing to pay. Thus, the determinants included in our model encompass a variety of socioeconomic and demographic characteristic, as well as any current knowledge or behaviors for reducing disease risks.

Our empirical model is specified as follows:

$$Y_{i,j} = \beta_{0,j} + \beta_{1,j} PRICE_i + \beta_{2,j} WATERFIRST_i + \beta_{3,j} (PRICE_i \times WATERFIRST_i) + \sum_n \beta_{n,j} X_{n,i} + \epsilon_{i,j} \quad (1)$$

Equation (1) represents a bivariate probit model that explores the drivers of household i's decisions regarding purchasing technology j (an air or water purifier). $Y_{i,j}$ is a binary variable that equals one if household i accepted the offer for technology j and zero otherwise; $PRICE_i$ is the randomized price offer faced by household i for both technologies;

$WATERFIRST_i$ is a binary variable that is equal to one if household i is randomly assigned Option A (the air frame, in which the first private technology was a household water purifier) and zero if the assignment is Option B; $X_{n,i}$ represents a series of n household-level socioeconomic, demographic, and behavioral controls (that is informed by the prior literature on the correlates of demand); and $\beta_{0,j}$ is a constant. We estimate this model for technologies j and j'; in line with our bivariate probit specification, the unobserved terms $\epsilon_{i,j}$ and $\epsilon_{i,j'}$ are jointly distributed as standard bivariate normal with correlation ρ.

In such a specification, the coefficients indicate the average effect of each of the explanatory variables on the probability of accepting the relevant price offer. Note, however, that we also interact the randomized price offer with the dichotomous variable indicating the household's option assignment.

The results of this estimation allow us to consider the relative importance of disease risk reduction complementarities relative to that of more commonly explored order and "embedding" effects, where the latter refers to the fact that stated WTP for a good may vary depending on whether it is evaluated on its own or as part of a more inclusive category (Kahneman and Knetsch 1992). In our case, this effect could arise from the fact that individuals were told to consider that they had already contributed to a health-risk reduction in one of the health domains through a mandatory community program, which might have led them to have systematically different willingness to pay for an additional health risk reduction in that domain, relative to the other second domain.

Thus, when $WATERFIRST_i = 0$ (the water frame, where the first private technology that is offered is an air purifier), our model reduces to

$$Y_{i,j} = \beta_{0,j} + \beta_{1,j} PRICE_i + \sum_n \beta_{n,j} X_{n,i} + \epsilon_{i,j}. \tag{2}$$

If, instead, $WATERFIRST_i = 1$ (the air frame, where the first private technology that is offered is a water purifier), the empirical model becomes

$$Y_{i,j} = \left(\beta_{0,j} + \beta_{2,j}\right) + \left(\beta_{1,j} + \beta_{3,j}\right) PRICE_i + \sum_n \beta_{n,j} X_{n,i} + \epsilon_{i,j}. \tag{3}$$

The coefficient $\beta_{2,j}$ may thus be interpreted as the marginal change in the probability of adopting technology j at a price of zero under the air frame (Option A). Similarly, the coefficient $\beta_{3,j}$ represents the marginal change in responsiveness of probability of accepting an offer to the product's price in the same situation. Several CVM studies—particularly those employing a dichotomous choice elicitation approach, where respondents are asked to simply accept or reject a particular proposal, as we do—have uncovered evidence of "order effects," where offering respondents a particular option first yields relatively higher WTP estimates (Boyle et al. 1993; Clark and Friesen 2008). However, as noted before, we are not aware of any attempt to simultaneously frame the elicitation question within the context of a related disease risk. For this reason, our expectations regarding the signs of $\beta_{2,j}$ and $\beta_{3,j}$ are not clear-cut.

4 Results

4.1 Sample Description

Table 2 presents descriptive statistics for our study sample of 862 households. The average household size is 5.6 people, and households are generally poor: nearly 80% report being below the poverty line, with an average monthly household expenditure across the sample of approximately $100. In addition, over 90% of households identify as belonging to one of India's historically disadvantaged castes or tribes. Only about 3% are headed by females. Access to electricity in the area appears to be low and unreliable, with only about 60% of respondents stating that they receive electricity at least "sometimes." Unsurprisingly, in the absence of dependable access to modern energy services, households spend on average fifteen hours per week collecting solid or other non-clean fuels every week. Combined with the time dedicated to collecting water, this burden is in excess of twenty hours per week.

Sample households also appear to be navigating a burdensome disease environment. For instance, nearly 7% of respondents report at least one case of childhood diarrhea in the two weeks prior to survey, while one in four household members report suffering from cough or cold symptoms over the same period. Households reporting illnesses spent approximately 11 and 9% of monthly expenditure to treat members' most recent episodes of cough/cold and diarrhea, respectively, and spent nearly five days sick with—or caring for someone suffering from—diarrhea.[2] Despite this nontrivial burden, rates of health-risk-averting behavior are low. For instance, only about 7% of respondents stated that they used an improved cookstove at least three to four times per week. Similarly, 70% of respondents did not take adequate measures to prevent their hands from coming into contact with stored drinking water in a household demonstration, as recommended by international drinking-water-quality guidelines (World Health Organization 2011).

The dearth of health-risk-averting behavior does not appear to be accompanied by a lack of knowledge in this sample. For example, 60% of households claim to have heard of ICS, while nearly all indicate that cooking smoke has negative effects. Similarly, almost all households state that diarrhea is preventable, and report having received a public health message related to water, sanitation, or hygiene in the past. Perceptions related to one's own drinking water and household air pollution levels, however, appear to be mixed: on an integer scale of one to ten—with ten representing "completely safe"—households identify the safety of their drinking water and household stove smoke as 6.4 and 4.6, respectively. The salience of individual diseases in respondents' minds also appears to be skewed: a surprisingly low proportion of respondents (just 6%) identified acute respiratory infections as more likely to be fatal, while nearly three times as many said the same for diarrhea.[3] These differences in perceptions related to health risks are likely to impact perceived benefits from making related risk-reduction investment and, thus, are a key motivation for this paper.

4.2 Estimates for Respiratory and Diarrheal Disease Risk Reductions with Simple Order Effects

We first run our WTP regressions allowing only for *constant shifts* in demand under different framing (i.e., excluding the $PRICE \times WATERFIRST$ interaction term that allows for differential price sensitivity). Columns 1–3 of Table 3 report results for the private air purifier, and columns 4–6 report the results for the private water purifier; all reported results explicitly allow for correlation in the water and air purifier purchase decisions. In model (1) of Table 3,

[2] About 20% of households reported no instances of cough or cold in the two weeks prior to the survey, while around half reported no instances of diarrhea over the same period. Averaging over all households, approximately 9 and 4% of monthly expenditure were spent treating the most recent bouts of cough/cold and diarrhea, respectively.

[3] The remainder (approximately 75%) stated that acute respiratory infections and diarrheal diseases are "equally dangerous."

we include only $PRICE$ and $WATERFIRST$ as explanatory variables. Consistent with economic theory, we find a negative and highly statistically significant relationship between $PRICE$ and the probability of accepting the air purifier offer. There is some evidence for an order effect, but it is not consistent across technologies. Respondents asked about the purchase of a water purifier before the air purifier are more likely to respond affirmatively to the offer for the former than those asked about the air purifier first. Meanwhile, those asked about the water purifier first are somewhat less likely to respond affirmatively to the offer for the air purifier, but that effect is weaker and not distinguishable from zero.

In models (2) and (3), we sequentially introduce an increasing number of controls related to household-level socioeconomic and demographic characteristics (in model 2); and then add disease and risk perceptions; current behavior related to safe or unsafe stove and water use; time spent cooking, or collecting fuel and water; and household history regarding other diseases (in model 3). The sign and significance of the price coefficient remains stable, as would be expected given that this was randomized at the household level. In addition, the inclusion of these controls leads to the coefficient for $WATERFIRST$ becoming significant at the 10% level in columns (2) and (3), hinting at the presence of a weak order effect. A number of other consistent patterns emerge.[4] We find that households with a higher average minimum level of adult education are more likely to accept the air purifier purchase offer. The more basic specification in model (2) reveals a positive relationship between the air purifier purchase decision and the number of rooms (a proxy for wealth). Finally, some practices and perceptions appear to play a role; households stating that they use clean fuels ($CLEANFUEL$) are more likely to purchase air purifiers, despite arguably "needing" them less, as are those that believed that respiratory illnesses are "most dangerous" ($ARIFATAL$) compared to diarrheal diseases.

Columns 4–6 reports the results from an identical set of regressions for the water purifier, once again controlling for constant, price-invariant, order effects. A similar story emerges with one notable exception, in that we observe a clear, consistent, and significant order effect in this case. Specifically, we find that $WATERFIRST$ is a positive and statistically significant predictor of the probability of accepting the offer. That is, households are more likely to accept the water purifier offer if they are presented with this technology before they receive the offer to purchase a private air purifier. Otherwise, higher prices make it less likely that households accept the water purifier offer; and more educated and larger households are more likely to accept the offer, as are households with a larger number of rooms. Practices and perceptions continue to matter—$CLEANFUEL$ and $ARIFATAL$ are, as before, positively related to the probability of accepting the offer.[5]

These results suggest that there is some evidence of a positive order effects (i.e., higher likelihood of saying yes to a price offer for initial offers than for subsequent improvements), but that the pattern is inconsistent, and appears to vary with the type of risk reduction. We return to this issue in Sect. 6.

[4] These patterns are entirely consistent when different groups of variables are excluded from model (3) (results not shown).

[5] Interestingly, neither of the water-related perceptions variables ($IMPROVEDWATER$ and $UNSAFEWATER$) are statistically significant predictors of the water purifier purchase decision, although they do have the "expected" signs. These results for perception variables suggest that clean-fuel use and consideration that respiratory diseases are particularly dangerous may simply be correlated with WTP for environmental health improvements in general, rather than indicating something specific about differential demand for respiratory versus diarrheal disease risk reductions.

Table 3 Bivariate probit regression results for WTP for air and water purifiers, with price-invariant order effects

VARIABLES	(1) ACCEPTAIR	(2) ACCEPTAIR	(3) ACCEPTAIR	(4) ACCEPTWATER	(5) ACCEPTWATER	(6) ACCEPTWATER
PRICE	−0.0226***	−0.0232***	−0.0233***	−0.0253***	−0.0267***	−0.0272***
	(0.00391)	(0.00390)	(0.00394)	(0.00318)	(0.00314)	(0.00320)
WATERFIRST	−0.169	−0.178*	−0.182*	0.211**	0.212**	0.231**
	(0.106)	(0.103)	(0.105)	(0.0937)	(0.0908)	(0.0903)
HHSIZE		0.0175	0.0213		0.0559**	0.0628***
		(0.0239)	(0.0259)		(0.0223)	(0.0234)
FEMALEHEAD		0.0339	0.155		−0.297	−0.225
		(0.241)	(0.241)		(0.258)	(0.280)
EDUCATION		0.0733***	0.0734***		0.102***	0.0964***
		(0.0178)	(0.0189)		(0.0143)	(0.0155)
ROOMS		0.109***	0.0718*		0.0786*	0.0612
		(0.0398)	(0.0405)		(0.0418)	(0.0428)
FARMER		0.0268	0.0852		0.0153	0.0494
		(0.104)	(0.105)		(0.0916)	(0.0941)
POVLINE		0.121	0.108		0.0171	0.00719
		(0.106)	(0.113)		(0.112)	(0.117)
ELECTRICITY		0.102	0.0166		0.0599	−0.00546
		(0.104)	(0.117)		(0.117)	(0.119)
HEARDWASH			−0.826			−0.159
			(0.629)			(0.519)
SMOKESAFETY			−0.00837			−0.0356
			(0.0251)			(0.0244)
VILLCLEAN			0.122			0.119
			(0.103)			(0.0981)

Table 3 continued

VARIABLES	(1) ACCEPTAIR	(2) ACCEPTAIR	(3) ACCEPTAIR	(4) ACCEPTWATER	(5) ACCEPTWATER	(6) ACCEPTWATER
ARIFATAL			0.368**			0.447***
			(0.187)			(0.164)
REGULARICS			0.245			0.307
			(0.226)			(0.244)
CLEANFUEL			0.268*			0.325**
			(0.142)			(0.141)
IMPROVEDWATER			0.144			0.0266
			(0.104)			(0.110)
UNSAFEWATER			−0.276***			−0.0537
			(0.102)			(0.117)
COOKTIME			−0.0153			−0.0111
			(0.0269)			(0.0180)
COLLTIME			0.00710*			0.00402
			(0.00380)			(0.00385)
WATERCOLL			−0.00405			0.0154
			(0.0120)			(0.0120)
HHTB			0.0361			−0.257
			(0.292)			(0.292)
CHILDDIARR			0.197			−0.0119
			(0.187)			(0.172)
Constant	0.449***	−0.581**	0.221	0.394***	−0.640**	−0.678
	(0.102)	(0.256)	(0.668)	(0.0893)	(0.307)	(0.619)
Observations	855	855	855	855	855	855

Standard errors—in parentheses—clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.3 Adding Price-Varying Order Effects

In Table 4, we report results for regressions similar to those reported in Table 3, except that we additionally allow for the order effects to vary with price (i.e., we include a $PRICE \times WATERFIRST$ interaction). The inclusion of this interaction term yields additional insights. Note first the difference in magnitudes of the coefficient on PRICE between the models shown in Table 3 and those in Table 4. As the inclusion of the $PRICE \times WATERFIRST$ interaction term allows us to identify changes in the relationship between the price and the probability of accepting the offer based on which device was offered first, the interpretation of the estimated coefficients changes, as shown in equations (2) and (3). Namely, in the case of the air purifier (water purifier), the coefficient $\beta^{AIR}_{PRICE} = -0.0188$ $\left(\beta^{WATER}_{PRICE} = -0.0208\right)$ is the price responsiveness of the probability of accepting the relevant offer when the private air purifier is offered first. This price sensitivity is considerably lower than that observed when the private water purifier is offered first; in that case the price sensitivity for the air (water) purifier is $\beta^{AIR}_{PRICE} + \beta^{AIR}_{PRICE \times WATERFIRST} = -0.0283$ $\left(\beta^{WATER}_{PRICE} + \beta^{WATER}_{PRICE \times WATERFIRST} = -0.0342\right)$. That is, the probability of accepting the offer for both devices is more price responsive when an offer to purchase the water filter comes first.

As noted before, the interpretation of the estimated coefficient for $WATERFIRST$ also changes with the inclusion of the interaction term; it is the marginal change in the probability of accepting the price offer if the price is zero. We find that $\beta^{WATER}_{WATERFIRST}$ is large, positive, and statistically significant. At the same time, while the coefficient on $\beta^{AIR}_{WATERFIRST}$ is negative, its magnitude is considerably smaller and it is never statistically significant. Together, this suggests that the air framing (i.e., when respiratory risks have been reduced by a community intervention) makes households *more* likely to purchase the water purification technologies without having a statistically meaningful impact on the corresponding demand for air purification technologies.

Collectively, these results provide evidence of a somewhat more nuanced order effect than that first uncovered in Table 3. Namely, it suggests a positive shift in the probability of accepting a price offer for technologies that reduce health risks broadly when the private water purifier is offered first. Specifically, in the case of the air this positive shift is almost exactly offset by a higher price sensitivity and the net effect on demand is weak at best. In contrast, for the water purifier, the positive shift is larger and the change in the price sensitivity is lower, such that a larger net increase in demand is apparent.

Most of the other results previously observed are robust to the inclusion of the interaction term. $CLEANFUEL$ and $ARIFATAL$ remain statistically significant and positive, with magnitudes that are largely the same; the same holds true for $EDUCATION$. The robustness of these findings across specifications increases our confidence in the stability of these correlations, and in the randomization of prices and question order across respondents.

5 Deriving Willingness to Pay

We can use our estimates to derive households' WTP for the proposed air purifier and water purifier technologies. Following Haab and McConnell (2002), given our basic probit specification (without a price-order interaction term), mean willingness to pay for each technology j (air purifier or water purifier) may be expressed as

$$WTP_j = -\frac{\beta_{0,j} + \beta_{2,j} + \sum_n \beta_{n,j} \bar{X}_n}{\beta_{1,j}}. \tag{4}$$

Table 4 Bivariate probit regression results for WTP for air and water purifiers, allowing for price-varying order effects

VARIABLES	(1) ACCEPTAIR	(2) ACCEPTAIR	(3) ACCEPTAIR	(4) ACCEPTWATER	(5) ACCEPTWATER	(6) ACCEPTWATER
PRICE	−0.0189***	−0.0187***	−0.0188***	−0.0196***	−0.0203***	−0.0208***
	(0.00451)	(0.00444)	(0.00439)	(0.00463)	(0.00459)	(0.00462)
WATERFIRST	−0.0249	−0.00420	−0.00867	0.432***	0.457***	0.479***
	(0.163)	(0.158)	(0.167)	(0.166)	(0.159)	(0.162)
PRICE × WATERFIRST	−0.00784	−0.00946	−0.00946	−0.0119*	−0.0132**	−0.0134**
	(0.00675)	(0.00665)	(0.00663)	(0.00646)	(0.00632)	(0.00643)
HHSIZE		0.0160	0.0189		0.0543**	0.0599**
		(0.0236)	(0.0258)		(0.0228)	(0.0238)
FEMALEHEAD		0.0558	0.180		−0.268	−0.191
		(0.241)	(0.241)		(0.263)	(0.286)
EDUCATION		0.0738***	0.0743***		0.102***	0.0978***
		(0.0175)	(0.0187)		(0.0143)	(0.0157)
ROOMS		0.112***	0.0750*		0.0822**	0.0656
		(0.0394)	(0.0401)		(0.0415)	(0.0425)
FARMER		0.0339	0.0921		0.0252	0.0593
		(0.103)	(0.105)		(0.0906)	(0.0937)
POVLINE		0.120	0.106		0.0153	0.00402
		(0.106)	(0.113)		(0.112)	(0.117)
ELECTRICITY		0.105	0.0201		0.0654	0.00154
		(0.104)	(0.117)		(0.117)	(0.119)
HEARDWASH			−0.856			−0.194
			(0.638)			(0.552)
SMOKESAFETY			−0.00968			−0.0374
			(0.0250)			(0.0239)
VILLCLEAN			0.116			0.110
			(0.103)			(0.0984)

Table 4 continued

VARIABLES	(1) ACCEPTAIR	(2) ACCEPTAIR	(3) ACCEPTAIR	(4) ACCEPTWATER	(5) ACCEPTWATER	(6) ACCEPTWATER
ARIFATAL			0.371**			0.449***
			(0.186)			(0.163)
REGULARICS			0.230			0.279
			(0.229)			(0.243)
CLEANFUEL			0.272*			0.332**
			(0.143)			(0.141)
IMPROVEDWATER			0.140			0.0212
			(0.104)			(0.110)
UNSAFEWATER			−0.282***			−0.0616
			(0.101)			(0.116)
COOKTIME			−0.0128			−0.00778
			(0.0281)			(0.0173)
COLLTIME			0.00700*			0.00390
			(0.00380)			(0.00379)
WATERCOLL			−0.00357			0.0160
			(0.0121)			(0.0120)
HHTB			0.0228			−0.281
			(0.288)			(0.289)
CHILDDIARR			0.195			−0.0137
			(0.187)			(0.173)
Constant	0.382***	−0.675***	0.163	0.292***	−0.773**	−0.772
	(0.116)	(0.262)	(0.682)	(0.110)	(0.311)	(0.644)
Observations	855	855	855	855	855	855

Standard errors—in parentheses—clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5 Willingness to pay for air and water purifier, USD per household per month

	MEAN†
Air purifier, $WATERFIRST$ unspecified‡	1.34
	(−0.33, 4.80)
Water purifier, $WATERFIRST$ unspecified‡	1.63
	(0.06, 4.97)
Air purifier, $WATERFIRST = 1$	1.09
	(−0.34, 4.12)
Air purifier, $WATERFIRST = 0$	1.68
	(−0.28, 6.38)
Water purifier, $WATERFIRST = 1$	1.91
	(0.77, 4.50)
Water purifier, $WATERFIRST = 0$	1.22
	(−0.77, 5.72)

†Bootstrapped 90% confidence intervals in parentheses. ‡PRICE × WATERFIRST interaction term not included in regression model

The inclusion of the interaction term somewhat modifies this expression. Specifically, when $WATERFIRST = 1$, mean willingness to pay is

$$WTP_j = -\frac{\beta_{0,j} + \beta_{2,j} + \sum_n \beta_{n,j}\bar{X}_n}{\beta_{1,j} + \beta_{3,j}}. \tag{5}$$

When $WATERFIRST = 0$, this expression reduces to

$$WTP_j = -\frac{\beta_{0,j} + \sum_n \beta_{n,j}\bar{X}_n}{\beta_{1,j}}. \tag{6}$$

Note that implicit in these expressions is the assumption that the demand curve for technology j is exponential.[6]

Table 5 reports our estimates for mean WTP. The estimates reported in the first two rows are obtained using models (3) and (6) in Table 3, i.e., they do not include a $PRICE \times WATERFIRST$ interaction term in the underlying regression specification. These estimates yield a WTP of \$1.34 per household per month for the air purifier, an amount that is nearly 20% less than the willingness to pay for the water purifier (\$1.63).

While useful in terms of gauging households' average valuation of these technologies—and, consequently, their valuation for the related disease risk reductions—not incorporating the interaction term masks the considerable variations in WTP that arise from the order in which the improvements were offered to respondents. In rows 3–4 and 5–6 of Table 5, we calculate WTP estimates from models (3) and (6) from Table 4, respectively. Two key conclusions may be drawn. First, the pattern observed in the first two rows of Table 5 continues to hold, i.e., when compared across analogous ordering scenarios, it is observed that households are willing to pay a substantial premium for the water purifier over the air

6 We assume an exponential demand curve primarily for empirical tractability and, in particular, to enable comparability of our estimates with the related literature that looks at WTP for environmental quality in low-income settings (e.g., Orgill et al. 2013). The results we present are qualitatively unchanged if we assume that demand for purification technologies is linear.

Table 6 Paired t test results for mean willingness to pay estimates

	Air purifier	Water purifier	Difference	(p-value)
$WATERFIRST$ unspecified‡	1.34	1.63	−0.30	0.00
$WATERFIRST = 1$	1.09	1.91	−0.82	0.00
$WATERFIRST = 0$	1.68	1.22	0.46	0.00
$WATERFIRST = 1/WATERFIRST = 0$	1.09	1.22	−0.13	0.00
$WATERFIRST = 0/WATERFIRST = 1$	1.68	1.91	−0.23	0.00

‡PRICE × WATERFIRST interaction term not included in regression model

purifier—specifically, up to 15% more.[7] Households' WTP for the water purifier is higher than that for the air purifier.

Second, households are most willing to pay for *both* goods jointly when $WATERFIRST = 1$, though the difference is not large. In other words, in the context of a hypothetical respiratory-illness-related community-level intervention and an offer to purchase the water purifier first (Option A), household perceptions of private benefits from both the water and air purifier appear to be jointly maximized.

Table 6 presents results from paired t tests, which indicate that the difference between each of these mean WTP amounts is statistically significant. Table 6 also illustrates that the higher WTP for the water purifier in our basic specification (a statistically significant difference of \$0.30) appears to be largely driven by the higher WTP for the technology when $WATERFIRST = 1$ (\$0.82), rather than when $WATERFIRST = 0$ (\$0.46). As a further test of the robustness of our results, we generate 1000 bootstrapped estimates of each of our WTP measures. This allows us to examine the extent to which our results are driven by our specific study sample.[8] The distributions of these bootstrapped estimates are shown in Fig. 3. A visual inspection of these distributions suggests that our results remain unchanged: mean WTP for the water purifier is higher than that for the air purifier (Fig. 3, panel a), and this higher WTP is almost entirely driven by the results in the air framing of Option A, which established a community-level respiratory risk reduction prior to the purchase offer for each of the private improvements (Fig. 3, panels b and c).

Note that while the nominal amounts may seem small, these are non-trivial sums in low-income contexts. Individually, for instance, WTP for each technology is approximately 1–2% of monthly household expenditure; taken together as an air-and-water-purifier bundle, this amounts to approximately 2–4% of monthly household expenditure. As a comparison, a frequently-quoted measure of affordability in the case of piped water access in developing countries is the so-called "five-percent rule," that is, improvements in access to water services via the provision of piped water are considered affordable and appropriate if the cost to households is approximately 5% of income (McPhail 1993).

[7] As the dichotomous variable $WATERFIRST$ captures the assignment of a scenario that is "mirrored" across technologies, the appropriate comparisons to make across the WTP estimates for air and water purifier are as follows: Air Purifier, $WATERFIRST = 1$ with Water Purifier, $WATERFIRST = 0$; and Air Purifier, $WATERFIRST = 0$ with Water Purifier, $WATERFIRST = 1$.

[8] Specifically, we bootstrap at the village level by randomly sampling villages from our original study sample. For each of 1000 bootstrapped samples of villages, we then repeat our analyses to obtain 1000 sets of results.

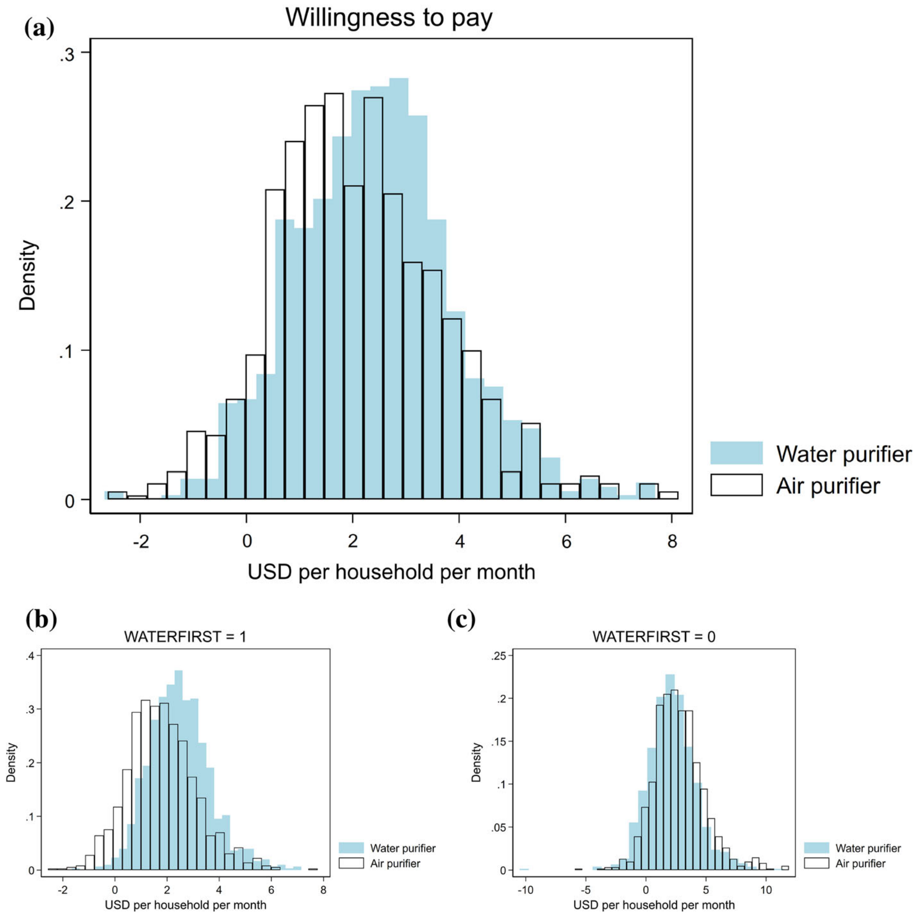

Fig. 3 Mean WTP for air and water purifier, USD per household per month—distribution of bootstrapped results **a** *WATERFIRST* unspecified, **b** *WATERFIRST* = 1 and **c** *WATERFIRST* = 0

6 Discussion

Prominent critiques of the contingent valuation method (e.g., Diamond and Hausman 1994) have focused on a distinct "order effect" in the results obtained from such surveys, whereby the stated WTP for an alternative is found to be higher when it is evaluated earlier in a sequence of multiple options. Others have identified an "embedding effect," in which stated WTP for a good varies depending on whether it is evaluated on its own or as part of a more inclusive category (Kahneman and Knetsch 1992). These concerns could be problematic for valuation of specific health technologies in low-income contexts, where households face multiple health risks. If, for instance, respondents are unable to determine which specific health risks are reduced using a particular technology (instead, treating them as "general" health-risk reduction devices), stated WTP for the technology may be biased upward. At the same time, the existence of multiple health risks may impact WTP for specific health risk reductions directly. For example, if the burden of disease imposed by household air pollution is a relatively small proportion of the total household-level disease burden, then the WTP a for reduction in air-pollution-related risks will likely be lower than if it had comprised a larger share of the total burden. This is because investments made to reduce specific health risks may do little to improve overall mortality or morbidity outcomes. Predictions about households' WTP for environmental health risk reductions using theoretical frameworks that consider multiple risks are therefore ambiguous (Jeuland et al. 2015d), and of limited use in guiding prioritization of different environmental and health policies.

Our unique study design allows us to consider these potential biases in contingent valuation surveys, and to investigate whether multiple disease interactions may influence households' preferences for disease-specific health-risk reductions. Our survey elicits private valuations for technologies that would reduce respiratory infection and diarrheal disease risks, the second and fourth leading contributors to the burden of disease globally (Murray and Lopez 2013), and two of the leading contributors to the global preventable environmental burden of disease. An overwhelming proportion of these illnesses affect people in low- and middle-income countries. Given that our sample is drawn from poor rural areas in Rajasthan, these risks are likely to be salient and distinct in our respondents' minds.

We find some evidence that the position of a specific technology in the sequence of two choices matters, but the significance of this effect is inconsistent across two different disease frames, which raises doubts about whether they arise from pure order effects. Indeed, as shown in Table 4, the order in which the two technologies are presented to respondents only appears to consistently matter for the water purifier. These results suggest that households' perceived private benefits from investments that mitigate diarrheal risks are greater than those that mitigate air pollution risks. Furthermore, the demand for the private water and air purifier is greatest when some of the health risk related to air pollution has previously been reduced by a community-level air quality improvement. This suggests that there may be important perceived complementarities in risk reductions when the less salient respiratory risk is reduced first at very low cost.[9] While these results warrant further empirical testing, they do suggest that the community-level disease context, with its multitude of risks, plays an important role in household-level health prevention behavior.

Our results point to a conceptualization of households' decisions about investing in private health-improving technologies as grounded in an understanding of the broader disease environment and associated health complementarities. Specifically, the private benefits that accrue to households from investing in private environmental health technologies depend crucially on the full set of risks the household faces. For instance, a water filter can lead to significant improvement in health outcomes if waterborne diseases are the key health risk faced by the household. That same water filter, however, may make little difference in households' health outcomes if households also face health risks related to malaria, tuberculosis,

[9] Because the disease frames were perfectly correlated with the order in which alternatives are presented to respondents, our interpretation of the results depends on the assumption that respondents took the information about the community-level intervention into account when answering the subsequent questions about the air and water purifier (though this is also of course a general critique of any stated preference design that assumes that respondents consider the information with which they are provided). As noted by a reviewer, respondents may have disregarded this information. In this specific instance, our results would not highlight the salience of complementarities in disease-risk reductions in respondents' minds. However, they would still provide informational value on (i) the relative importance households in rural India place on air- and water-based risk reductions; and (ii) an upper bound for their WTP for technologies that achieve these risk reductions on their own (because their budget constraints bind less). That said, we do not believe respondents ignored the information about the community-level intervention. That we observe the typical "order effect" result seen in the literature (whereby respondents are more likely to accept a price offer for alternatives presented earlier in the sequence) consistently only for the water purifier suggests that disease frame and, in turn, complementarities in disease-risk reductions matter. A more complete experiment would also have randomly varied the inclusion of the community-level risk reduction programs, but budget and sample size limitations prevented us from including the two additional arms that would have been required to test this formally.

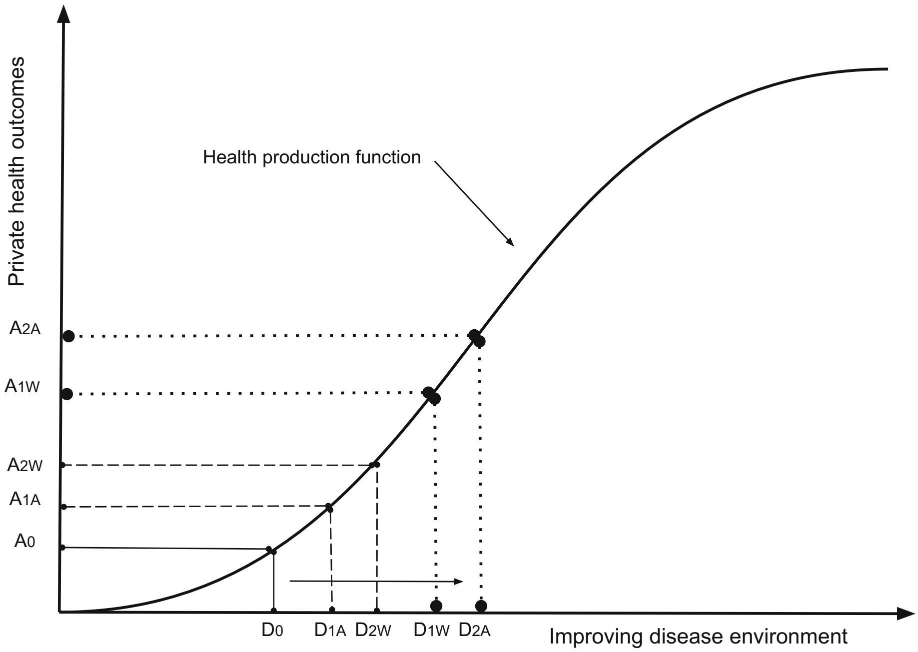

Fig. 4 Health production function and decisions to invest in health technologies

and air pollution. Consequently, households' demand for the technology across these two situations may be very different.

More formally, this may be represented as in the S-shaped health production function shown in Fig. 4. Imagine that a community-level air quality intervention is perceived to improve the disease environment from a baseline of D_0 to D_{1A}, considerably more than that from D_0 to D_{1W} due to a community-level water quality intervention. Under these two very different reference points, additional investments in household-level water and air filters that further improve the disease environment—reducing each disease risk by equal amounts—may lead to very different improvements in health. Specifically, the acquisition of a water filter given a community-level air quality intervention further improves the disease environment from D_{1A} to D_{2W} while that of an air filter given a community-level air quality intervention improves it from D_{1W} to D_{2A}. The corresponding perceived increase in private health outcomes in these two scenarios is $(A_{2W} - A_{1A})$ and $(A_{2A} - A_{1W})$, respectively. As shown in Fig. 4, $(D_{2W} - D_{1A}) = (D_{2A} - D_{1W})$; however, $(A_{2W} - A_{1A}) > (A_{2A} - A_{1W})$. In other words, an equivalent improvement in the disease environment may be perceived to lead to a lower improvement in health outcomes depending on where one believes one is along the health production function. Assuming households' willingness to pay is proportional to perceived health benefits, willingness to pay for a technology that provides an equivalent improvement in the disease environment would be different in the two cases.

A rigorous exploration of why perceptions of multiple risks and preferences may be aligned in ways that leads to such perceived complementarities—especially given the fact that the burden of disease due to lower respiratory infections is estimated to be greater than that due to diarrheal diseases in low-income communities—is beyond the scope of this paper. It may be the case that individual episodes of diarrhea, which predominantly impacts young children, are identified more distinctly by caregivers and key decision-makers within the household. In contrast, adults also bear a relatively high burden of disease due respiratory ailments (Lozano et al. 2012). That an overwhelming majority of respondents in our sample indicate that both—respiratory infections and diarrheal diseases—are "equally dangerous" (73%) and "equally important to reduce" (87%) while 53% indicate that diarrhea is "worse" for children under five years old suggests that many perceive children to have greater relative sensitivity to diarrhea.

7 Conclusion

Households in low-income settings face a multitude of risks across different health domains. This can lead to low demand for health technologies that only reduce health risks in a single disease domain if they fail to sufficiently reduce overall mortality or morbidity rates. Using a unique contingent valuation survey design, we evaluate the extent to which health-risk reductions in one health domain impact willingness to pay for environmental health technologies in another domain. Specifically, we focus on respiratory infections and diarrhea—two diseases that are responsible for a large proportion of the global burden of disease, much of it disproportionately in low- and middle-income countries. We find that conditional on having already mitigated some of the health risks related to air pollution via a hypothesized community-level intervention, households are more (less) willing to make additional private health investments that mitigate risks related to diarrheal diseases. In contrast, households' willingness to pay for private technologies to reduce air-quality-related risks conditional on having mitigated community-level water-quality risks is considerably lower. Consistent with these results, we provide evidence on household-level perceptions that suggests that diarrheal diseases are a more salient source of health risks for households, and that perceived private benefits from diarrheal risk reductions outweigh those from comparable reductions in risks due to air pollution.

Our results have important implications for policymakers and practitioners working to improve environmental health outcomes in low-income settings. In particular, interventions that aim to promote technological solutions to reduce "domain-specific" health risks may fail to achieve widespread success in settings characterized by health risks in multiple domains. In these cases, implementers may be able to enhance effectiveness of interventions by combining solutions that address risks in multiple domains in potentially cost-effective ways (for instance, by providing bundles of complementary technologies that address distinct health risks).

It is also worth noting that the source of many of the health risks faced by the poor in low-income settings is well beyond the confines of the household. The capacity of individuals to reduce these risks using household-level interventions is often constrained, such as in the case of ambient air pollution, which may require action at the community or regional level to see improvements. Optimal policies in these instances would need to recognize both household-level constraints and the potential for health-risk complementarities in innovative ways.[10] We believe this presents a fruitful avenue for policy-relevant research going forward, especially in low-income settings.

[10] For instance, a nominal fixed surcharge assessed as part of a household's water tariffs may, counterintuitively, make households more likely to connect to the water network (and reduce water-quality-related health risks) if proceeds from this surcharge are used to drive efforts to reduce complementary health risks in other domains. Utility payments, however, are not relevant in the context of rural Rajasthan, where a more straightforward payment vehicle–charging fees directly for the provision of specific risk-reducing technologies–may be most appropriate. We note, however, that at the community scale, even these simple payment approaches may require efforts to overcome collective action problems related to collective payments.

Appendix

A Survey Scenarios

The following pages, extracted from the English translation of our survey instrument, provide additional insight about the two scenarios—Option "A" and "B"—randomly allocated to survey respondents.

Option A. I want you to imagine that there was a program instituted in your community – at a small cost to you of 50 Rs. per year – which reduces the risk of respiratory illness in your community. This program would involve installing a device at a nearby industry that would reduce the smoke and air pollution it produced. This air pollution is harmful to health in your community, because it increases the risk of respiratory illness. The device would have no other effects in your community excep t for reducing respiratory illness. For example, instead of 3 out of every 20 people in your community becoming ill with respiratory disease every 2 weeks, with this device, only 2 of eve ry 20 people in your community would become ill with this disease every 2 weeks.***(Enumerator: Please show card A1)*** Everyone in your community would be forced to contribute 50 Rs. to the purchase of this device by the village chief; there would be no exceptions.

This program would not affect diarrheal disease at all. But you could reduce diarrhea in your family by spending your own money on a water purification device. As shown in this picture, this device would decrease the 2-week diarrhea risk for each person in your family without changing anything else about the wat er, but it would cost you **300 / 1000** Rs. per year.***(Enumerator: Please show card A2)*** I want you to think carefully about whether you would purchase this device. When you think about this, you should consider your household budget and the other things that you could do with this money, if you did not spend it on the water purification device. Please answer the way you feel.

H.5. Remember, you already paid 50 Rs. for a community air pollution program. Now I want to know: Would you pay **300 / 1000** Rs. per year for this water purification device?
[0] No ***(Continue)*** [1] Yes ***(Skip to H.7)*** [-9] Don't know / not sure ***(Continue)***

H.6. Why would you <u>not</u> purchase this device? ***(Multiple answers possible)***
[1] It is too expensive / I have no money
[2] I have more important things to spend money on
[3] Someone else should pay
[4] My family risk is low
[5] I do not believe the device will work
[6] I do not like the device
[-9] Don't know / not sure
[-95] Other, please specify: ______________

H.7. How certain are you of your choice?
[1] Very certain [2] Certain [3] Somewhat certain [4] Not certain [-9] Don't know / not sure

H.8. Now I'd like you to imagine your decision to buy the water purification device for **300/1000 Rs.** ***(Show card A2)*** without the community air pollution program, <u>so you would not pay 50 Rs.and your respiratory risk</u> would not change. Would you buy the water purifier, which will reduce your family's risk of dia rrhea, if the community air pollution program is not institututed?
[0] No [1] Yes [-9] Don't know / not sure

H.9. Now I want to know how your decision in the previous question (H.8) would change if the compulsory community air pollution program was again present in your village ***(show respiratory risk reduction in card A1).*** How would your decision change? Would you be more or less likely to buy the water purifier, which reduces diarrhea ***(show card A2 again)***, for your family for **300/1000** Rs?

[0] No change [1] More likely [2] Less likely

Now I want you to make a second choice, which would further decrease your family's risk of <u>respiratory</u> disease. You could do th is by spending your own money on an air purifier for your home that would remove contaminants from the air in your house. This device would allow you to decrease your respiratory r isk without changing anything else about the air in your house, but it would again cost you **300 / 1000** Rs. per year.***(Enumerator: Please show card A3)***

H.10.Remember, you already paid 50 Rs. for a community air pollution program. Now I want to know: Would you pay **300 / 1000** Rs. per year for this air purification device?
[0] No ***(Continue)*** [1] Yes ***(Skip to H.11)*** [-9] Don't know / not sure

H.11. Why would you <u>not</u> purchase this device?
[1] It is too expensive / I have no money
[2] I have more important things to spend money on
[3] Someone else should pay
[4] My family risk is low
[5] I do not believe the device will work
[6] I do not like the device
[-9] Don't know / not sure
[-95] Other, please specify: ____________________

H.12. How certain are you of your choice?
[1] Very certain [2] Certain [3] Somewhat certain [4] Not certain [-9] Don't know / not sure

H.13. Now I'd like you to imagine your decision to buy the air purifier for **300/1000 Rs.** ***(Show card A3)*** *without* the community air pollution program, <u>so you would not pay 50 Rs.and your respiratory risk</u> would not change. Would you buy the air purifier, which will reduce your family's risk of respiratory dis ease, if the community air pollution program is not institututed?
[0] No [1] Yes [-9] Don't know / not sure

H.14. Now I want to know how your decision in the previous question (H.13) would change if the compulsory community air polluti on program was again present in your village ***(show respiratory risk reduction in card A1).*** How would your decision change? Would you be more or less likely to buy the air purifier for your family, which reduces respir atory risk (***show card A3 again)***, for **300/1000** Rs?
[0] No change [1] More likely [2] Less likely
(Skip to Section I) ____

Option B. I want you to imagine that there was a program instituted in your community – at a small cost to you of 50 Rs. per year – which reduces the risk of diarrhea illness in your community. This program would involve installing a device at all community drinking water sources that would reduce the contami nants in the water you drink. This device would have no other effects in your community except for reducing diarrheal disease. For example, instead of 2 out of every 20 people in y our community becoming ill with diarrheal disease every2 weeks, with this device, only 1 out of every 20 people in your community would become ill with this disease every 2 weeks. ***(Enumerator: Please show card B.1)*** Everyone in your community would be forced to contribute 50 Rs. to the purchase of this device by the village chief; there would be no exception s.

This program would not affect respiratory illness at all. But you could reduce respiratory illness in your family by spending y our own money on an air purifier for your home that would remove contaminants from the air in your house. This device would allow you to decrease your respiratory risk without changing anything else about the air in your house, but it would cost you **300 / 1000** Rs. per year. ***(Enumerator: Please show card B.2)*** I want you to think carefully about whether you would purchase this device. When you think about this, you should consider your household budget and the other things that you could do with this money, if you did not spend it on the ai r purification device. Please answer the way you feel.

H.15. Remember, you already paid 50 Rs. for a community water pollution program. NowI want to know: Would you pay **300 / 1000**Rs. per year for this air purification device?
[0] No ***(Continue)*** [1] Yes ***(Skip to H.17)*** [-9] Don't know / not sure

H.16. Why would you <u>not</u> purchase this device?
[1] It is too expensive / I have no money
[2] I have more important things to spend money on
[3] Someone else should pay
[4] My family risk is low
[5] I do not believe the device will work
[6] I do not like the device
[-9] Don't know / not sure
[-95] Other, please specify: ___________________

H.17. How certain are you of your choice?
[1] Very certain [2] Certain [3] Somewhat certain [4] Not certain [-9] Don't know / not sure

H.18. Now I'd like you to imagine your decision to buy the air purifier for **300/1000 Rs** ***(Show card B2)*** without the community water pollution program, so you would not pay compulsory 50 Rs. Would you buy the air purifier, which will reduce your family's risk of respiratory disease, if the community water pollution program is not institututed?
[0] No [1] Yes [-9] Don't know / not sure

H.19. Now I want to know how your decision in the previous question (H.18) would change if the compulsory community water pollu tion program was again present in your village ***(show diarrheal risk reduction in card B1).*** How would your decision change? Would you be more or less likely to buy the air purifier, which reduces respiratory disease ***(show card B2 again)***, for your family for **300/1000** Rs?

[0] No change [1] More likely [2] Less likely

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