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## Awareness and the Demand for Environmental Quality: Drinking Water in Urban India*


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# Awareness and the Demand for Environmental Quality: Drinking Water in Urban India*

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*Abstract*

The demand for environmental quality is often presumed to be low in developing countries due to poverty. Less attention has been paid to the possibility that lack of awareness about the adverse health effects of environmental pollution could also keep the demand low. We use a household survey from urban India to estimate the effects of awareness and wealth on home water purification. Average costs of different home purification methods are used to get estimates on willingness to pay for better drinking water quality in Delhi. We find that measures of awareness such as schooling and exposure to mass media have statistically significant effects on adoption of different home purification methods and therefore, on willingness to pay. These effects are similar in magnitude to the wealth effects.

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## 1. Introduction

The demand for environmental quality—clean air, potable water, sanitation, safe food—is often presumed to be low in developing countries due to poverty and this is considered to be efficient since it reflects choices made by individuals in their own best interests. However, individuals in developing countries often lack the necessary information to make good decisions about environmental hazards in their day-to-day lives.

In this paper we show that even if households can afford to take private measures to improve their environmental quality, very often they choose not to do so, because they are not aware of the health risks associated with inferior environmental quality.

Contaminated drinking water is a major health hazard in developing countries and diarrhea is the most common disease associated with it. This is particularly true for the poor and the vulnerable. The World Health Organization (WHO, 2002) estimates 1.7 million deaths and 54.2 million disability adjusted life years (DALYs) lost worldwide per year due to unsafe water, hygiene and sanitation.[1] Almost all of these deaths are in developing countries and nine out of ten deaths occur in children. In India alone, there are more than a million child deaths per year resulting from waterborne diseases like diarrhea (Parikh et. al., 1999).

Interventions to improve drinking water quality and minimize exposure to health risks from ingestion of contaminated water include provision of quality regulated piped water supply to all households. According to a WHO (2002) estimate, if universal piped and regulated water supply were achieved, 7.6 billion diarrhea cases could be averted annually worldwide. However, such state intervention is unlikely to be forthcoming in the short-run, especially in the absence of a clearly expressed demand from the public, which in turn depends on public awareness of the health hazards of drinking contaminated water.

[1] One DALY being equal to the loss of one healthy life year.

A substitute short-term solution is dis-infection at point of use. This includes low-grade technologies like straining with a cloth, using chlorine and safe storage vessels, to relatively more sophisticated and expensive technologies like electronic filters that use ultra-violet radiation to remove pathogens etc. These interventions have large health impacts in regions of high child mortality and some are inexpensive. Straining with a cloth for example, especially if it is folded over to form eight or more layers, has been shown to be successful in removing copepods, which are a host for cholera bacteria (Colwell *et. al.*, 2003).

The question is why has adoption of safe drinking water practices not been universal? Poverty is an important factor but it certainly cannot explain lack of use of even costless methods like straining with a cloth. According to a study in rural Bolivia, cited in Gadgil (1998), many people were unaware of the link between water contamination and diarrhea. Undoubtedly, awareness is a determinant of the demand for safe drinking water. In this paper we estimate the magnitude of the "awareness" effect and compare it to that of wealth.

We use measures of schooling, exposure to mass media, and occurrence of diarrheal disease as indicators of a household's awareness about the health risks associated with drinking contaminated water. The first two are self-explanatory. Regarding the third, it is possible that a household afflicted with waterborne diseases in the past will take some steps to improve its quality of drinking water to reduce the likelihood of such disease in the future.

While we are not aware of any previous research specifically examining the effect of awareness on water purification in developing countries, studies on demand for water have found evidence that education is one of the determinants. Dasgupta (2001) and McConnell and Rosado (2000) use data from Delhi and an urban area in Brazil respectively to show that education of the household head is statistically significant in a household's decision to purify its drinking water controlling for income and other household characteristics.[2,3] When formulating public health policy however, it is important to distinguish whether information is gathered through formal schooling, the mass media, or knowledge gained through experience of a previous health shock. This is what we do in this paper ─ we examine the role of different sources of knowledge in adoption of environmental risk averting behavior by households.

We summarize the main findings of our paper here. Each of the awareness indicators included in the analysis has an independent (of household wealth effects) significant effect on a household's decision to adopt some home purification method. The magnitudes of these effects are by no means small and are comparable to the wealth effects. For example, a one-year increase in the years of schooling of the most educated female member of the household increases the probability of home purification by about 1.4 percentage points. Since this variable ranges from 0 to 23 years, its effect is comparable in magnitude to the increase of 24.6 percentage points resulting from a move from the first to the fourth wealth quartile. The probability of purification rises by 8 percentage points if a female household member reads a newspaper at least once a week. A prior bad health experience raises the probability that households boil their drinking water by about 5 percentage points.

Finally, using estimated probabilities of the different methods of purification from the econometric model, and average costs of the different methods from an informal survey of markets in the metropolitan city of Delhi, we calculate the expected cost of improving household water quality for the sampled households in Delhi. Our estimates

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[2] Alberini *et. al.*'s (1996) study of diarrhea and avoidance behavior through hand-washing in Jakarta, Indonesia, does not show any significant effect of mother's education on either diarrhea or avoidance behavior. In their study, boiling drinking water was pervasive, reflecting its low cost owing to the fuel subsidies in Jakarta. This is very far from being the case in urban India. Another related study is the one by Larson and Gnedenko (1999) of home water purification in Moscow, in which, again the cost of boiling is low, and protection from pathogens does not appear to be the main concern.

[3] There are also plant or community-level studies of industrial pollution such as that of Pargal and Wheeler (1996) who relate the level of schooling in a community and other variables to the pollution level from plants in the neighborhood. In one of their specifications, schooling significantly reduces pollution, perhaps reflecting collective action that pressures the plant to lower pollution. Evidence from the US, also at the community level (Brooks and Sethi, 1997) or at the state level (Boyce *et. al.*, 1999) indicates that schooling seems to lower pollution levels.

indicate that expected willingness to pay increases by nearly 50 percent from Rs. 212 per person per year to Rs. 314 when the schooling of the most educated female in the household rises from 3.5 to 10.5 years. By comparison the expected willingness to pay rises from Rs. 212 to Rs. 289 when moving from the second to the third wealth quartile. It rises by over 25 percent when a woman member of the household reads a newspaper at least once a week.

The following section describes the data and reports summary statistics. Sections 3 and 4 present the results from bivariate probit and multinomial logit models respectively that are used to estimate the role of awareness in the household's decision-making process for home purification of drinking water. Section 5 estimates willingness to pay for households in the city of Delhi. Section 6 concludes.

## 2. Data

We use data from the National Family Health Survey of India, (NFHS), conducted by the International Institute for Population Sciences in 1998-1999. The NFHS sample covers 99 percent of India's total population living in 25 out of 26 states (Tripura and union territories were not included) and is a household survey with an overall target sample size of approximately 90,000 ever-married women in the age group 15-49.[4]

The sample households are evidently highly exposed to waterborne disease. One of the survey questions asked whether there were any cases of diarrhea among children aged 0-3 years in the two weeks preceding the survey. Of the 7,351 households that had children in this age group, 1,014 or 14 percent reported at least one case in the preceding two weeks.

[4] We included only urban households with 15 or fewer members. Furthermore, we exclude households for which some variables were missing. Accordingly we retain 20,681 of the 25,243 households in the original sample.

Among the households who treat their drinking water, four different methods are used– (i) straining water with an ordinary cloth, (ii) using alum (aluminum sulphate, a flocculant) tablets, (iii) using an ordinary (candle) filter, (iv) using an electronic filter or (v) boiling water. The choices are mentioned in ascending order of their cost.[5,6]

As mentioned earlier, straining with a cloth folded over to form at least 8 layers can provide significant protection against cholera, though most free-floating bacteria would pass through the mesh (Colwell *et. al.*, 2003).[7]

Water can also be treated with flocculants like potassium and aluminum sulfates. Flocculants cause small particles including bacteria to form clumps that can be allowed to settle or that can be filtered using ordinary filters. These filters are also effective in reducing turbidity and in large reductions in bacterial and other pathogens like giardia, amoebae, etc. However, ordinary filters do not themselves disinfect water adequately i.e. will not remove all fecal pathogens.

Electronic filters first filter particulate matter and then irradiate the water with ultraviolet light, killing all pathogens. Provided they are maintained well, electronic filters are as effective as boiling at removing pathogens. Electronic filters impart no taste or odor to the water, and consume far less energy than boiling water does.

Boiling is the oldest method to obtain drinking water free of biological contaminants. In many developing countries, residents routinely boil their water because they perceive their water supply to be unsafe for drinking purposes. The World Bank estimates that 1 percent of Jakarta's GDP is spent on boiling drinking water.

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[5] We do not consider treatment to remove chemicals from drinking water. While chemical contamination is important in certain localities, in poor countries like India, the main adverse health effects from water contamination are due to biological contamination from pathogens that originate from fecal matter (Gadgil, 1998).

[6] Costs are calculated in Appendix A.

[7] In the same study, a large number of mothers using cloth purification reported a decline in the incidence of diarrhea within families.

In our analysis, for households using more than one method of purification, we have considered only the 'best' method (in terms of removal of pathogens from the water) and we have clubbed together households using alum tablets or ordinary filters because there were very few households using the former in our sample.[8] Furthermore, given that the NFHS does not report the percentage of total drinking water consumption that a household purifies, we assume that a household's entire drinking water consumption is treated.

Table 1 reports purification adoption rates for households with different characteristics. Despite the high exposure to diarrheal disease, a significant 47 percent of households continue to consume water without using any type of water purification method. This percentage remains as high as 32 percent even for households in the top wealth quartile.[9] Furthermore, only about 20 percent of households use methods (i.e. boiling and electronic filters) that reliably remove commonly found biological pathogens.[10]

[ **Insert Table 1 here** ]

There is no direct information in the NFHS about how informed a household is regarding the health risks arising from drinking contaminated water. But our hypothesis is that if the adult members of a household, who are presumably the decision makers, are educated, it is likely that they will be aware of the health risks associated with drinking non-potable water. We therefore use education of adult members to proxy for health awareness of households. The NFHS collected information on the educational qualifications of individuals. We use highest number of years of education among female

[8] We have arbitrarily ranked electronic filtration to be more effective than boiling. Since very few households engage in both, this particular choice is unlikely to make any difference to the results.

[9] We explain below how data on wealth are constructed.

[10] Less than 3 percent of households who use some purification method use an electronic filter. It is only in the last few years that there has been a proliferation of such products both in terms of availability in the market and usage by consumers.

household members aged $15^+$, and highest number of years of education among male household members aged $15^+$ to capture education levels of adult male and female members in the household.

Table 1 shows that the proportion of households who do not purify their water is smaller for households with higher adult human capital stocks. However, even among households whose adult members are highly educated (i.e. have $14^+$ years of education), 25-30 percent do not use any water purification method and even among those who adopt some method, about 40 percent use methods that are not fully effective in removing biological pathogens from the water.

The NFHS does not collect information on consumption or income. However, the survey collects information on household ownership of various assets (car, motorcycle, bicycle, refrigerator, telephone, color television, black and white television, radio, mattress, clock or watch, table, chair, etc.) and characteristics of household dwelling (house type, toilet type, number of rooms per capita, source of light, fuel type, utensils type, etc.). We use the first principal component of these variables as a wealth index. Appendix *A* provides the formula for the wealth index. Filmer and Pritchett (2001) used an almost identical index from the first round of the NFHS and found that it explained consumer expenditure data quite well.

The first principal component explains 24.36 percent of the variation in the asset variables. For ease of interpretation, we create and use wealth quartiles from the wealth index rather than the actual wealth index in our analysis.[11] Households in the bottom quartile correspond to the poorer units in the sample.

One concern is that our wealth index is not comprehensive so the information/awareness variables could still act as a proxy for unobserved wealth effects. To examine the plausibility of this speculation, we created another index with all the

[11] We did estimate a bivatiate probit model with the wealth index rather than its quartiles. The coefficients on the awareness variables changed very little.

variables used earlier together with the education variables mentioned above. Spearman's rank correlation coefficient (ρ=0.9878) between the two indices shows that the ranking of the households changes very little with or without the education variables in the wealth index.

Simple descriptive statistics suggest important wealth effects in the adoption of water purification methods. Households belonging to the upper wealth quartiles used costly purification methods like an ordinary water filter or alum, electronic filter, or boiling. Thus while 2.64 percent of households in the bottom quartile used alum tablets or an ordinary filter, this number increases to 30 percent in the upper-most quartile. Nearly two-thirds of households in the bottom wealth quartile used no water purification method; in the fourth quartile, this proportion was less than a third. Electronic filters were primarily used by households in the top wealth quartile. (See Table 1 for further details).

Mass media in India often report on episodes of waterborne diseases and precautions that can be taken especially during the rainy season when incidence of such diseases increase. Government agencies sponsor social awareness messages relating to prevention of waterborne diseases in the media. Since the NFHS collects data on women's exposure to such mass media, we include variables like whether any female member of the household reads a newspaper, watches television, or listens to the radio at least once a week in our specifications.[12]

Among households not exposed to the print media, sixty percent do not treat their water. This proportion falls by half for households that read newspapers. This differential was somewhat less stark for two of the other media variables: watching TV and/or listening to the radio at least once a week.

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[12] We also include whether any female member of the household goes to the cinema at least once a month in our analysis but this variable was not significant in practice.

Lastly, it is plausible that a household's perception about the health risks from drinking unsafe water is influenced by a health "shock" in the past that can be related to poor drinking water quality. That is, households learn from a bad health experience and their willingness to adopt safe drinking water practices increases. We use occurrence of diarrhea in the two weeks preceding the survey, in the age group 0-3 years to measure household's exposure to waterborne diseases. This variable incorporates some information, albeit quite limited, on household morbidity due to drinking water quality.

We also include other control variables: state dummies, demographic characteristics (household size, household head's age, age squared, and marital status, proportion of household members in age groups 0-3 years, 3-5 years, and 5-15 years, socio-economic variables (religion and caste dummies, proportion of household members in different occupations (those not working, in occupations that (do not) require higher education, in medical professions, and in the service sector)), place of treatment when ill and source of water dummies, (whether piped into home, a public tap, or other source such as a handpump or borewell).[13,14]

Descriptive results reported in this section suggest strong unconditional correlations between household's demand for improved quality of drinking water and the different awareness indicators. However, many of these variables are highly correlated with each other and the observed patterns based on estimated unconditional correlations could be misleading. We thus need to develop an econometric model where we are able to separate the individual effects of each of the above variables from the others. We do this in the next two sections.

[13] As some of the states few observations, we clustered them with other states based on geographic, socio-economic and cultural proximity.

[14] Jalan and Ravallion (2002) find that provision of piped water to a household is not adequate to prevent diarrhea among children. Prevention rates are higher if the infrastructure (piped water) is combined with the stock of human capital of household members particularly those of the female members.

### 3. Bivariate Probit Model

A household's perception of the health risks from drinking water and therefore its purification behavior, could be affected by its past experience of water-borne disease. Of course, its experience of diarrhea will be conditional on its purification behavior. To allow for this, we begin by estimating a bi-variate probit model of purification and occurrence of diarrhea among 0-3 year olds in the household.[15]

We have data on incidents of diarrhea among 0-3 year olds in the two weeks preceding the day of survey that we use as a proxy for prior incidence of diarrhea. We want to assess whether a household's decision to purify water by any means depends on its information/awareness about the advantages of improving the quality of water, independently of the household's wealth status.

Our estimated econometric specification is:

$$\begin{aligned}
&y_1^* = \beta_1' x_1 + \varepsilon_1,\ \ y_1 = 1 \quad if \quad y_1^* > 0,\ 0\ otherwise \\
&y_2^* = \beta_2' x_2 + \varepsilon_2,\ \ y_2 = 1 \quad if \quad y_2^* > 0,\ 0\ otherwise \\
&E(\varepsilon_1) = E(\varepsilon_2) = 0 \\
&Var(\varepsilon_1) = Var(\varepsilon_2) = \sigma^2 \\
&Cov(\varepsilon_1, \varepsilon_2) = \rho
\end{aligned} \tag{1}$$

The binary variables $y_1$ and $y_2$ are indicators for whether or not a household adopts any home purification of water, and whether or not a 0-3 year old in the household has been afflicted by diarrhea in the two weeks preceding the survey. $x_i$'s are the vector of explanatory variables (described in Section 2 above) that includes the wealth, education and media exposure variables and $u_i$'s are correlated, identically distributed random variables. We estimate this model using maximum likelihood techniques. The correlation coefficient between the errors of the two equations is statistically significant (the Likelihood Ratio Test for $H_o$: $\rho=0$ against $H_1$: $\rho \neq 0$ gave a p-value of 0.0329) thus

[15] Ideally we would have liked to include the incidence of diarrhea among all household members but this information is not available in the data.

rejecting the hypothesis that the two dependent variables are not jointly determined. The results are reported in Table 2.[16]

**[Insert Table 2 here]**

The probability of purification is 7 percent greater for households in the second as compared to the first wealth quartile, and as much as 24.5 percent greater for those in the fourth as compared to the first quartile. Educational attainments of adult household – male or female – members are also important in the household's decision to purify water. A single additional year of education among the highest educated female (male) adults in the household will increase the probability of using some method of purification by 1.4 (1.0) percentage points. Two of the media dummies: whether any female household member reads a newspaper at least once a week, and whether she listens to the radio at least once week, are statistically significant. It should be noted that even though possession of a television or radio are components of the wealth index, they are included independently in the specification so that watching TV and listening to the radio do not proxy for ownership of these media.

A different specification in which the wealth index was included directly in place of quartile dummies yielded very similar coefficients and marginal effects for the awareness variables. We also estimated a model that included interactions between the wealth quartiles and other variables, but nearly all the interaction terms were statistically insignificant and the coefficients of interest were very similar.

The second column of Table 2 reports the marginal effects on the probability of the occurrence of diarrhea. Only wealth is statistically significant.

[16] Household water purification and occurrence of diarrhea are assumed to be jointly determined in this estimation procedure.

## 4. Multinomial Logit Model

To study the effects of awareness on willingness to pay for water quality, we need to allow for the fact that different purification methods have different costs. To examine this, we estimate a multinomial logit model where a household has five different choices available – no purification, straining with a cloth, alum tablets or ordinary (candle) water filter, electronic filtration, or boiling.

Let $Y_{ij}^*$ be the $i^{th}$ household's utility from making the $j^{th}$ purification choice for $j$ = 0,1,2,3,4 where $j$ = 0 denotes the choice of not purifying. The observed choice of $j^{th}$ purification method used by the $i^{th}$ household is defined as:

$$Y_{ij} = 1 \qquad \text{if } Y_{ij}^* = Max(Y_{i0}^*, Y_{12}^*, ..., Y_{i4}^*) \qquad (2)$$
$$= 0 \text{ otherwise}$$

The intuition underlying this model is that a household faced with many alternatives makes a single decision depending on which alternative gives it the highest utility.

The underlying latent variable is specified as:

$$Y_{ij}^* = \beta_j' x_i + \varepsilon_{ij} \qquad (3)$$

where $x_i$ is the vector of observed household characteristics, and $\varepsilon_{ij}$ is a residual that captures unobserved household characteristics and errors in optimization by the household. The $\varepsilon_{ij}$'s are assumed to be identically and independently distributed with Type I extreme-value distribution. It is assumed that the household chooses only one type of purification method.[17] Standard numerical optimization algorithms can be used to estimate the model.

[17] In the data however, some households may have indicated adoption of more than one purification method. In order to cut down the number of alternatives we have ranked the different purification methods and assumed that the household adopts the most effective (in terms of removing pathogens) method.

Finally, we have to allow for the endogeneity of occurrence of diarrhea. Given that estimating a simultaneous equation multinomial model is computationally very burdensome, we use a two-stage procedure. In the first stage a logit model of the probability of getting diarrhea among 0-3 year olds as a function of the explanatory variables in the previous model as well as the following additional variables: knowledge of adult women regarding oral re-hydration (ORS) products (whether a woman has heard of ORS before, recognizes the ORS packet, used ORS), recognition of symptoms of diarrhea by women (repeated watery stools and vomiting, blood in stools etc.), is estimated. In the second stage, the multinomial logit model is estimated in which the predicted probability from the logit model is included as a regressor in addition to the explanatory variables from the previous model.

The estimated coefficients in the multinomial model are difficult to interpret. We need to calculate the marginal effects for the variables of interest (i.e. the change in the probability of adoption of a particular alternative with a unit change in the explanatory variables) which are not only functions of their own estimated coefficients but also depend on all other estimated coefficients and levels of regressors. The analytical expressions for the marginal effects are for any *m=0,..,4*:

$$\frac{\partial P(Y=m\,|\,\mathrm{X})}{\partial x_k} = P(Y=m\,|\,\mathrm{X}).[\beta_{mk} - \sum_{j=0}^{4} \beta_{jk} P(Y=j\,|\,\mathrm{X})] \text{ , if } x_k \text{ is continuous} \qquad (4)$$

$$\frac{\Delta P(Y=m\,|\,\mathrm{X})}{\Delta x_k} = P(Y=m\,|\,\mathrm{X}, x_k=1) - P(Y=m\,|\,\mathrm{X}, x_k=0) \text{, if } x_k \text{ is discrete}^{18} \qquad (5)$$

The response probabilities are given by:

$$P(Y=m) = e^{\beta_m' x} \Big/ 1 + \sum_{j=1}^{4} e^{\beta_j' x} \qquad \textit{for } m = 1,2,3,4 \qquad (6)$$

$$P(Y=0) = 1 \Big/ 1 + \sum_{j=1}^{4} e^{\beta_j' x} \qquad (7)$$

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[18] In case of categorical explanatory variables we report the change in probability of adoption of a particular alternative with a change from one state to another.

In expressions (10) and (11), $\beta_m$ is the coefficient associated with the m$^{th}$ choice in the multinomial logit model.

The analytical standard errors of the marginal effects for our sample (20,681 observations) and model (more than 20 explanatory variables) are computationally very burdensome to calculate. Hence, we bootstrap our multinomial model to estimate the associated standard errors. We use a sample size of 20,000 observations and 50 repetitions in our computations.

We now turn to the results from the multinomial logit model. In the first stage logit equation of occurrence of diarrhea among 0-3 year olds, the variables serving as excluded regressors from the second stage, knowledge of the household members regarding oral rehydration products (whether member has heard of ORS before, recognizes the ORS packet etc.), recognition of symptoms of diarrhea by household members (repeated watery stools and vomiting, blood in stools etc.) are highly statistically significant. The estimated pseudo $R^2$ is very high for cross-sectional data at 0.52. Using this model we compute the estimated probability of occurrence of diarrhea that we use in the second-stage multinomial model of the different purification methods.

Our estimates of the multinomial logit model are reported in Table 3. The first column reports the estimated marginal effects of the different variables on the probability of no purification evaluated at the means of the explanatory variables. In congruence with the bivariate probit model, relative to the bottom-most wealth quartile, households in the other three quartiles are more likely to adopt some kind of purification method to improve their quality of drinking water.

**[Insert Table 3 here]**

In the bivariate probit model, our unconditional marginal effects for purification showed a strong relationship between whether a household adopts a water purification method and both the wealth position and the "knowledge stock" of the household. Is this pattern also observed across different purification methods?

Use of a costless but inferior purification method like straining with a cloth is less likely in the top quartile of the wealth distribution. Wealth has a large effect on the household's decision to adopt a purification method that entails some cost to the household. For example, relative to the bottom wealth quartile, the probability of an average household in the second quartile using a candle filter/alum to purify its water is 6 percentage points greater, and the same difference is 25 percentage points for the upper most wealth quartile. For the most expensive and common method of purification – boiling – we observe a similar trend where the marginal effects rise as we move up the wealth quartiles although not by as much.

We also want to test whether controlling for wealth, knowledge acquired by adult members through formal education leads to the household adopting superior methods of purification. Table 3 indicates that our education variables are significant with the education of the female adult members being the dominant effect. These effects are large: a *single* additional year of female education increases the probability of boiling by 1 percentage point compared to an effect of 0.47 due to an increase of one year of education among male adult members.

Among the media exposure variables used as proxies to capture transmission of knowledge to households through targeted information, listening to the radio and reading the newspaper are significant. It is interesting that for a cost-free purification method like straining with a cloth, female members listening to the radio is likely to increase the probability by 1.4 percentage points while for boiling, the probability increases by 3 percentage points.

The health experience proxy that we have used in our analysis—occurrence of diarrhea among 0-3 year olds—is not significant for any of the purification methods except for boiling and electronic filter. Again this result is not unexpected since these two methods are the only ones that kill all bacteria.

Finally, in addition to the above variables, as mentioned in the data section we also included several control variables in our model. While details of their effects on the different home purification methods are available from the authors, it is worthwhile to comment on the effects of the occupation dummies. Model estimates suggest that households where the head works in the medical sector (surgeons, physicians, nurses etc.) are more likely to use alum tablets and or the ordinary filter compared to the others. However, there are no statistically significant effects of working in the medical sector on adoption of other purification methods.

## 5. **Expected willingness to pay for potable drinking water**

From a policy perspective, it is important to get an estimate of willingness to pay (WTP) for safe drinking water. Is it the case that better informed people are willing to pay more for a better quality environmental commodity than the uninformed? However, the NFHS was not designed as a contingent valuation survey nor does it collect information that will allow us to get an estimate of the household's willingness to pay. We can however use the probabilities predicted by the multinomial model and our calculated costs for the different methods of purification to estimate the lower bound that each household is willing to pay for safe drinking water.

We collected cost information on different brands of electronic filters, ordinary filters and alum tablets from a survey of local markets in the metropolitan city of Delhi.[19] Under certain assumptions and based on the average cost price of these technologies, we estimated an annual per person cost of purification. The details on the assumptions made are spelt out in *Appendix B* of the paper. According to our estimates boiling is the most expensive method of improving the quality of drinking water. On the other hand, even though our data shows that use of electronic filter is not common in our sample, it is less

[19] We thank Dwiraj Bose for conducting the survey.

than half as expensive as boiling and if maintained properly, improves the quality of water to the same extent as boiling does.

Let $C_{ij}$ be the actual cost associated with the outcome $j$ for household $i$. We assume that $C_{ij} = C_j \ \forall \ i$ i.e., cost of purification method $j$ is constant over the entire population for each of the four purification methods. Under this assumption, $C_j$ at best can be interpreted as the lower bound for willingness to pay by households for purification method $j$. The expected lower bound of willingness to pay ($EW_i$) by $i^{th}$ household is given by:

$$EW_i = C_0 * P(Y_i = 0) + C_1 * P(Y_i = 1) + C_2 * P(Y_i = 2) + C_3 * P(Y_i = 3) + C_4 * P(Y_i = 4) \quad (8)$$

$P(Y_i=j)$ for $j$=0,1,2,3,4 is the associated estimated probability of adoption of purification method $j$ for the $i^{th}$ household from the multinomial model. We assume that all decision makers within the household will have identical $P(Y_i=j)$'s.

Using the sub-sample of households from Delhi only, estimated costs and probabilities of adoption of different purification methods, we estimate the (lower bound of) per person mean willingness to pay to improve the quality of water as Rs. 303 and per person median willingness to pay is Rs. 304 per year. ($US 1 = Rs. 46.)

How do these willingness to pay estimates relate to household wealth, education and media exposure variables? We report two sets of statistics. We fix values of all variables other than the variable of interest at their mean levels and report the expected willingness to pay. We thereby isolate the effects of the specific variable of interest from other household characteristics. We call this the "controlled" WTP. This is reported in the first column in Table 4. We also report the mean willingness to pay for different categories without controlling for household characteristics. For this latter case we report the mean, median and the standard deviation.

**[Insert Table 4 here]**

The controlled willingness to pay more than doubles from Rs 158 in the bottom wealth quartile to Rs. 329 in the top quartile. Median willingness to pay increases ten-fold between the bottom and top wealth quartiles from Rs. 44 to Rs. 451.

The adult education variables have comparable effects. Median willingness to pay in the lowest category for maximum female education, no education, is Rs. 81, while for the highest category of 14+ years of education, it is Rs 497. The increase in median willingness to pay between no education and 1-7 years of education and no education and 8-13 years of education is greater for female than male education.

The controlled WTPs show a similar trend.[20] The controlled WTP is lower in households where female members are uneducated compared to households where male members are illiterate. Furthermore the slope for female education years is steeper than that for education among males. For example, when number of years of education among female members increases from 3.5 to 10.5 years, WTP increases by 50 percent. However, for males the corresponding number is 21 percent. These numbers would probably support a view existing in the literature that men tend to judge health risks to be much smaller and less problematic than women do (WHO, 2002 (page 35)).

Reading a newspaper is the most influential mass medium in terms of changing individual health risk perceptions associated with drinking unsafe water. The median willingness to pay is Rs. 451 and is comparable to the expected willingness to pay of the wealthiest and the most educated in the sample. This is also considerably higher when compared to the willingness to pay—Rs. 144—for improved quality of drinking water by the sample of households where female members do not read a newspaper even once a week. The difference between willingness to pay for a better quality environmental good among households exposed to the other two mass media—watching TV and listening to the radio once a week—compared to households not exposed to such mass media is equally significant.

[20] For both education variables, the controlled WTP's are evaluated at no education, at 3.5, 10.5 and at 17 years of education respectively.

The controlled WTPs for the media variables show a large difference between households where female members read a newspaper and where they do not—WTP is nearly 40 percent higher in households where female members read a newspaper at least once a week! The impacts of the other two media variables on WTP are less significant. Table 4 reports the details on these statistics.

**[Insert Figures 1-4 here]**

Figures 1-4 depict the kernel densities associated with estimated willingness to pay for the different wealth quartiles, for different years of education across genders and for exposure to mass media. The pictures depict very clearly that expected willingness to pay for improved quality of drinking water rises with the wealth quartiles, with more education and with greater exposure to media variables.

**[Insert Figures 5-6 here]**

Figures 5-6 show the wealth and education effects on the WTP.[21] Across each wealth quartile, an additional year of education for female members increases the household's willingness to pay for better quality water more than it does with an additional year of education for male members in the household. Furthermore, moving from no education to 10 years of education (the middle of the range) roughly doubles the expected WTP, which is about the same as the increase resulting from a move from the bottom to the third wealth quartile.

## 5. Conclusion

Poor environmental quality leads to individuals facing serious health risks in their everyday lives. Individuals will adopt measures to improve their environmental quality

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[21] In these graphs to separate out the effects of the two variables of interest, the values of all other regressors are at their mean levels.

only if they perceive the associated health risks and if they can afford to pay for the prevention measure. It is the role of awareness as separate from the income constraint that we try to evaluate in this paper in the context of drinking water in urban India.

Household's awareness about health and hygiene can be raised through formal education and through education imparted (directly and indirectly) by the media. Our results show that there are statistically significant, and quantitatively non-negligible effects of wealth on demand for better quality of environmental goods. However, we also find that there is a strong and comparable effect of education attainment of household members and their exposure to mass media messages through newspapers or radio. This suggests that the common presumption that awareness in comparison to income has a second-order impact on the demand for environmental quality needs to be questioned more generally. Vocal public awareness campaigns to educate the population about the health risks associated with consuming environmental goods of inferior quality may be an important policy instrument.

*Appendix A*: **Construction of the wealth index**

The wealth index for the $i^{th}$ household is defined as:

$$w_i = \sum_{j=1}^{32} f_j \left[ \frac{a_{ij} - m(a_j)}{s_j} \right] \quad \forall i = 1,.., N$$

In the above equation,

$$a_{ij} \quad = 1 \text{ if } i^{th} \text{ household has asset } a_j,$$

$$= 0 \text{ otherwise},$$

$$m(a_j) = \frac{\sum_{i=1}^{N} a_{ij}}{N},$$

$$s_j = \sqrt{\frac{\sum_{i=1}^{N} a_{ij}^2}{N} - [m(a_j)]^2} \quad ,$$

and $f_j$ is the "scoring factor" for the $j^{th}$ asset, that is, ($f_1$ ,…, $f_{32}$) maximizes the variance of $w$ subject to the constraint $\sum_{j=1}^{32} f_j^2 = 1$.

### *Appendix B*: Estimated costs of different purification methods in city of Delhi

*Straining*: We assume that a household does not have to spend any money if it adopts straining its drinking water with cloth as its chosen water purification method.

*Alum tablet*: Each alum tablet costs a rupee and can be used to purify 10 liters of water. Assuming a per person daily consumption of drinking water to be 2 liters (this assumption is maintained throughout our cost estimates for the different purification methods), the estimated annual average cost for each person is Rs.73 if the household uses alum tablets as its chosen water purification method.[22]

*Ordinary filter*: Based on a survey of retail shops in Delhi, the average cost price of an ordinary candle filter with a volume capacity of 25 liters is assumed to be Rs.500. In addition, the candles have to be replaced every three years at the cost of Rs.50 for each candle. (Typically these filters come with two candles). Assuming a discount rate of 10 percent and an expected life of the filter to be 10 years, per person annual average cost is estimated to be Rs.110.47. The corresponding estimates under assumptions of 4 and 6 years of expected life of the filter are Rs.276.49 and Rs.237.46 respectively.

*Boiling*: We assume that a calorie of heat is required to raise the temperature of 1 ml. of water by 1 degree Celsius, the efficiency of a gas stove is 53.6 percent, the calorific value of liquid petroleum gas is 10,600 calories/gram and that there is no heat lost due to improper container. We do not factor in the fixed cost of the gas stove or the container used for boiling in our estimates. Under the above assumptions, if the initial temperature of water that is to be boiled is 25 degrees centigrade, the average annual cost per person of boiling water is estimated to be Rs.1635.20. Under the same assumptions but different initial water temperatures (20 and 30 degrees centigrade), the estimated costs are Rs.1744.70 and Rs.1525.70 respectively.

*Electronic filter*: Based on a survey of retail shops in Delhi, the average cost price of an electronic candle filter is assumed to be Rs.5,100. In addition, a cost of Rs.250 is incurred towards its maintenance per year for the filter to be effective in killing the possible pathogens in the water. Assuming a discount rate of 10 percent and an expected life of the filter to be 10 years, per person annual average cost is estimated to be Rs.791.53. The corresponding estimates under assumptions of 4 and 6 years of expected life of the filter are Rs.1534.33 and Rs.1116.72 respectively.

[22] A daily per capita consumption of 2 liters is the generally accepted value for a person weighing 60 kg. (Gadgil, 1998). This is the value used in estimating ingestion exposure to potentially hazardous chemicals in drinking water. The actual water intake, however, varies considerably from individual to individual, and also according to climate, physical activity and culture.

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## Table 1: Purification adoption rates for various household characteristics

| | No purification | Purification | | | |
|---|---|---|---|---|---|
| | | Straining | Alum/ordinary filter | Electronic filter | Boiling |
| *Wealth*: | | | | | |
| Bottom quartile | 66.16 | 19.48 | 2.64 | 0.08 | 11.64 |
| Second quartile | 50.16 | 22.32 | 7.08 | 0.24 | 20.16 |
| Third quartile | 41.56 | 20.84 | 15.92 | 0.48 | 21.20 |
| Top quartile | 31.96 | 11.36 | 28.96 | 5.12 | 22.60 |
| *Highest number of years of education among adult female household members*: | | | | | |
| No education | 68.84 | 20.67 | 2.71 | 0.10 | 7.67 |
| 1-7 years | 54.98 | 23.35 | 6.69 | 0.23 | 14.74 |
| 8-13 years | 42.57 | 17.87 | 15.36 | 1.07 | 23.13 |
| $14^+$ years | 26.32 | 11.68 | 30.31 | 5.49 | 26.20 |
| *Highest number of years of education among adult male household members*: | | | | | |
| No education | 67.67 | 16.37 | 4.90 | 0.31 | 10.74 |
| 1-7 years | 59.86 | 22.30 | 4.51 | 0.12 | 13.22 |
| 8-13 years | 48.19 | 20.20 | 10.83 | 0.68 | 20.10 |
| $14^+$ years | 30.19 | 13.57 | 28.48 | 4.36 | 23.40 |
| *Exposure to mass media*: | | | | | |
| Doesn't read newspaper once a week | 60.45 | 19.96 | 6.37 | 0.37 | 12.85 |
| Reads newspaper at least once a week | 32.12 | 16.79 | 22.26 | 2.79 | 26.04 |
| Doesn't watch TV once a week | 62.73 | 19.81 | 3.80 | 0.19 | 13.48 |
| Watches TV at least once a week | 44.08 | 18.22 | 15.83 | 1.77 | 20.10 |
| Does not listen to radio once a week | 53.16 | 21.15 | 10.53 | 1.10 | 14.07 |
| Listens to radio at least once a week | 41.55 | 15.76 | 16.90 | 1.87 | 23.91 |
| All households | 47.45 | 18.50 | 13.66 | 1.48 | 18.90 |

Note: The sample consists of 20,681 households from urban India in 1998-99.

**Table 2: Marginal effects for the bivariate probit model**

| | Probability of purification | Probability of occurrence of diarrhea |
|---|---|---|
| Wealth quartile 2 | 0.0724*<br>(0.0124) | -0.0033*<br>(0.0014) |
| Wealth quartile 3 | 0.1255*<br>(0.0147) | -0.0037*<br>(0.0017) |
| Wealth quartile 4 | 0.2458*<br>(0.0167) | -0.0058*<br>(0.0022) |
| Maximum years of education among female members | 0.0143*<br>(0.0012) | -0.0000<br>(0.0002) |
| Maximum years of education among male members | 0.0096*<br>(0.0014) | -0.0001<br>(0.0001) |
| Female members read newspaper at least once a week | 0.0807*<br>(0.0122) | -0.0003<br>(0.0015) |
| Female members watch television at least once a week | 0.0051<br>(0.0125) | 0.0025<br>(0.0016) |
| Female members listen to the radio at least once a week | 0.0340*<br>(0.0096) | 0.0003<br>(0.0013) |
| Number of observations | 20,681 | |
| Log likelihood | 13,386.38 | |

Standard errors reported in parentheses. * indicates significance at 5 percent or lower.

## Table 3: Marginal effects of the multinomial logit model

| | No purification | Straining | Alum or ordinary water filter | Electronic filter | Boiling |
|---|---|---|---|---|---|
| Wealth quartile 2 | -0.1113* | 0.0120 | 0.0581* | 0.0025 | 0.0387* |
| | (0.0162) | (0.0077) | (0.0260) | (0.1318) | (0.0151) |
| Wealth quartile 3 | -0.1965* | 0.0047 | 0.1409* | 0.0025 | 0.0485* |
| | (0.0181) | (0.0077) | (0.0361) | (0.1337) | (0.0174) |
| Wealth quartile 4 | -0.3052* | -0.0392* | 0.2488* | 0.0207 | 0.0750* |
| | (0.0248) | (0.0099) | (0.0521) | (0.1374) | (0.0207) |
| Maximum years of education among female members | -0.0161* | -0.0002 | 0.0061* | 0.0005* | 0.0097* |
| | (0.0015) | (0.0006) | (0.0008) | (0.0002) | (0.0011) |
| Maximum years of education among male members | -0.0100* | 0.0006 | 0.0050* | 0.0004* | 0.0041* |
| | (0.0014) | (0.0006) | (0.0007) | (0.0001) | (0.0010) |
| Female members read newspaper at least once a week | -0.0776* | 0.0049 | 0.0291* | 0.0011 | 0.0425* |
| | (0.0119) | (0.0068) | (0.0051) | (0.0007) | (0.0089) |
| Female members watches television at least once a week | -0.0104 | 0.0094 | 0.0032 | 0.0005 | -0.0027 |
| | (0.0153) | (0.0062) | (0.0093) | (0.0010) | (0.0131) |
| Female members listens to the radio at least once a week | -0.0401* | 0.0142* | -0.0044 | -0.0003 | 0.0306* |
| | (0.0085) | (0.0055) | (0.0052) | (0.0004) | (0.0084) |
| Children 0-3 years afflicted with diarrhea in last two weeks at time of survey (predicted) | -0.0263 | 0.0124 | -0.0365 | 0.0038* | 0.0467* |
| | (0.0308) | (0.0135) | (0.0288) | (0.0017) | (0.0239) |
| Observed frequencies | 9,814 | 3,827 | 2,825 | 306 | 3,909 |
| Number of observations | | | 20,681 | | |
| Log likelihood | | | -15,830.89 | | |

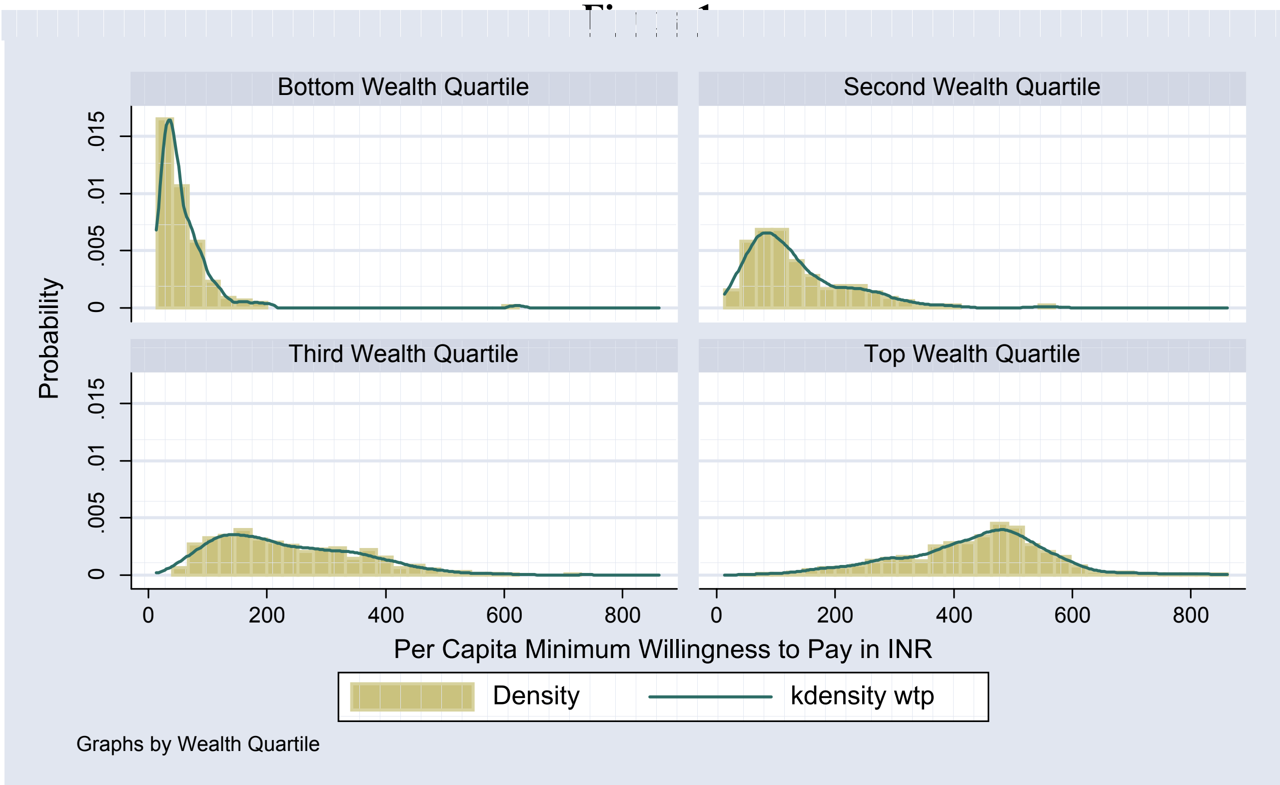
Standard errors reported in parentheses. * indicates significance at 5 percent or lower.

## Table 4: Descriptive statistics for expected willingness-to-pay for Delhi (lower bound in Indian rupees)

| | Controlled WTP | Mean WTP | Median WTP | Standard deviation |
|---|---|---|---|---|
| *Wealth*: | | | | |
| Bottom quartile | 158 | 59 | 44 | 56 |
| Second quartile | 218 | 136 | 110 | 86 |
| Third quartile | 252 | 235 | 214 | 119 |
| Top quartile | 329 | 434 | 451 | 124 |
| *Highest number of years of education among adult female household members*:* | | | | |
| No education | 171 | 91 | 81 | 61 |
| 1-7 years | 212 | 178 | 155 | 108 |
| 8-13 years | 314 | 343 | 351 | 132 |
| $14^+$ years | 426 | 497 | 501 | 93 |
| *Highest number of years of education among adult male household members*:* | | | | |
| No education | 210 | 108 | 71 | 114 |
| 1-7 years | 232 | 139 | 111 | 104 |
| 8-13 years | 281 | 277 | 270 | 151 |
| $14^+$ years | 328 | 462 | 480 | 121 |
| *Exposure to mass media*: | | | | |
| Does not read newspaper at least once a week | 243 | 174 | 144 | 119 |
| Reads newspaper at least once a week | 309 | 429 | 451 | 130 |
| Does not listen to radio at least once a week | 57 | 226 | 195 | 154 |
| Listens to radio at least once a week | 65 | 369 | 402 | 171 |
| Does not watch TV at least once a week | 58 | 138 | 97 | 115 |
| Watches TV at least once a week | 61 | 320 | 327 | 175 |

Controlled WTP: Willingness to pay of the different sub-samples (e.g. bottom wealth quartile) keeping all other variables in the at their mean levels
Mean and median WTP: Respective sample descriptive statistics of the expected WTP
*For the two education variables, the controlled WTP is evaluated at 0, 3.5, 10.5 and 17 years of education to represent the four categories (no education, 1-7, 8-13 and $14^+$ years of education) respectively

## Figure 1




## Figure 2

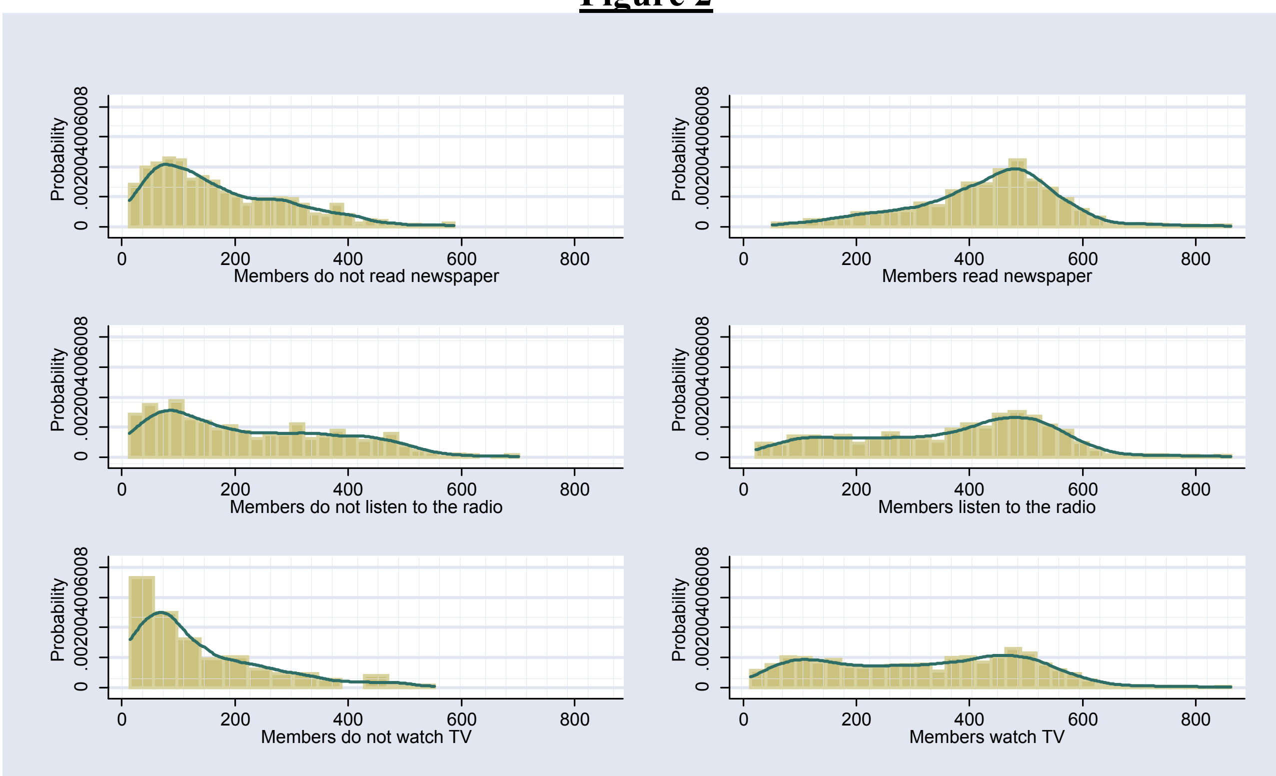


Figure 3

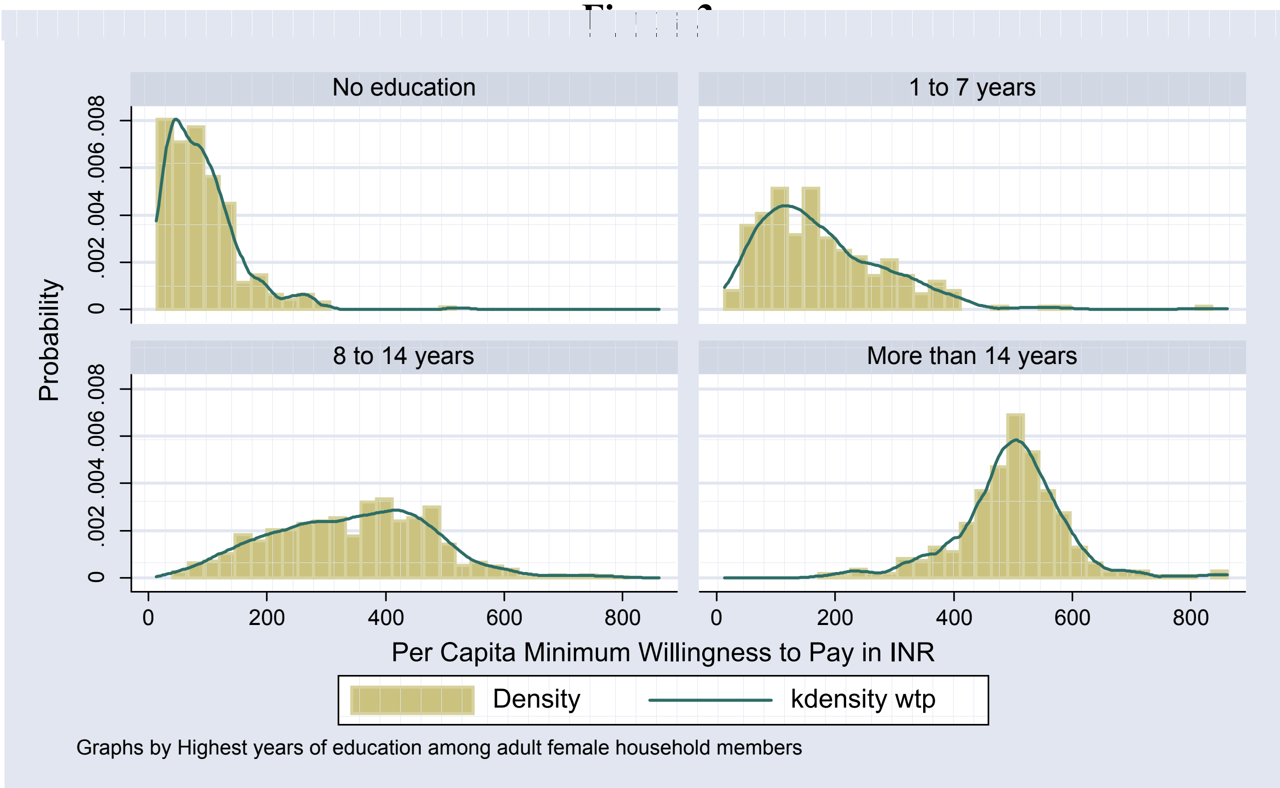
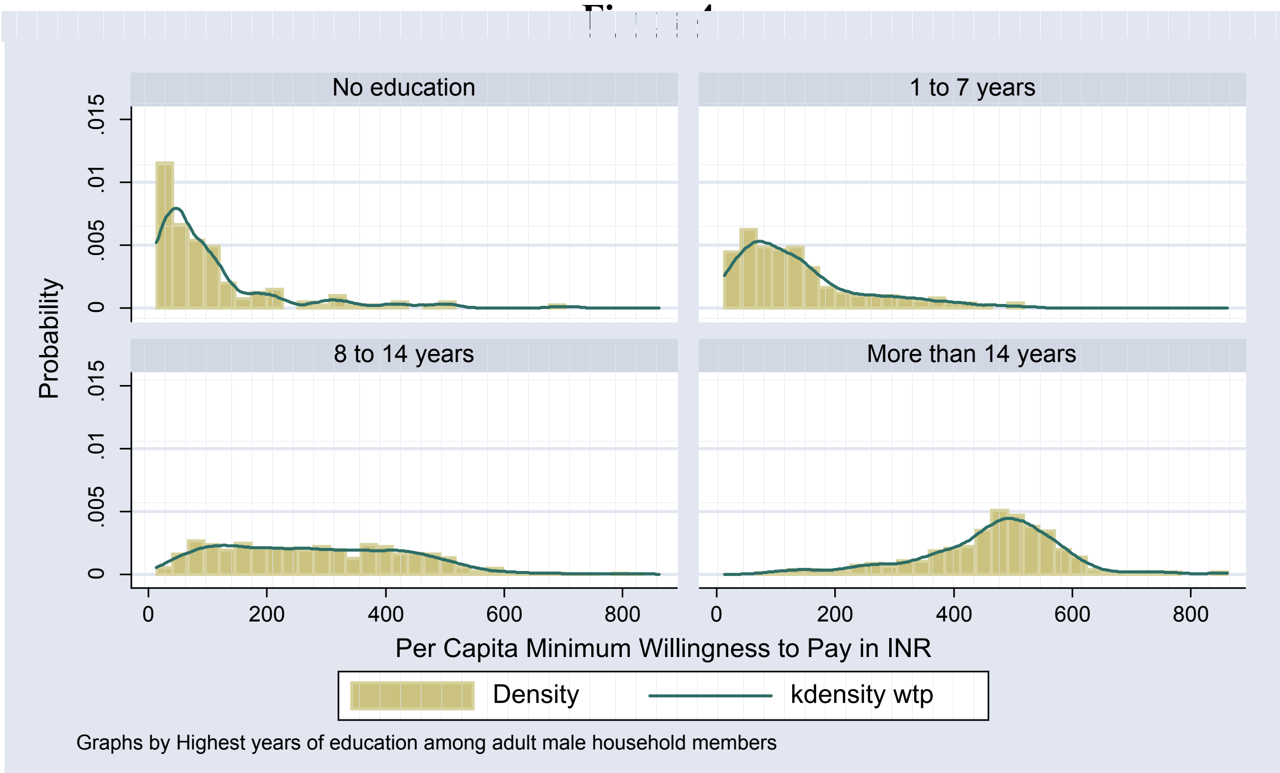
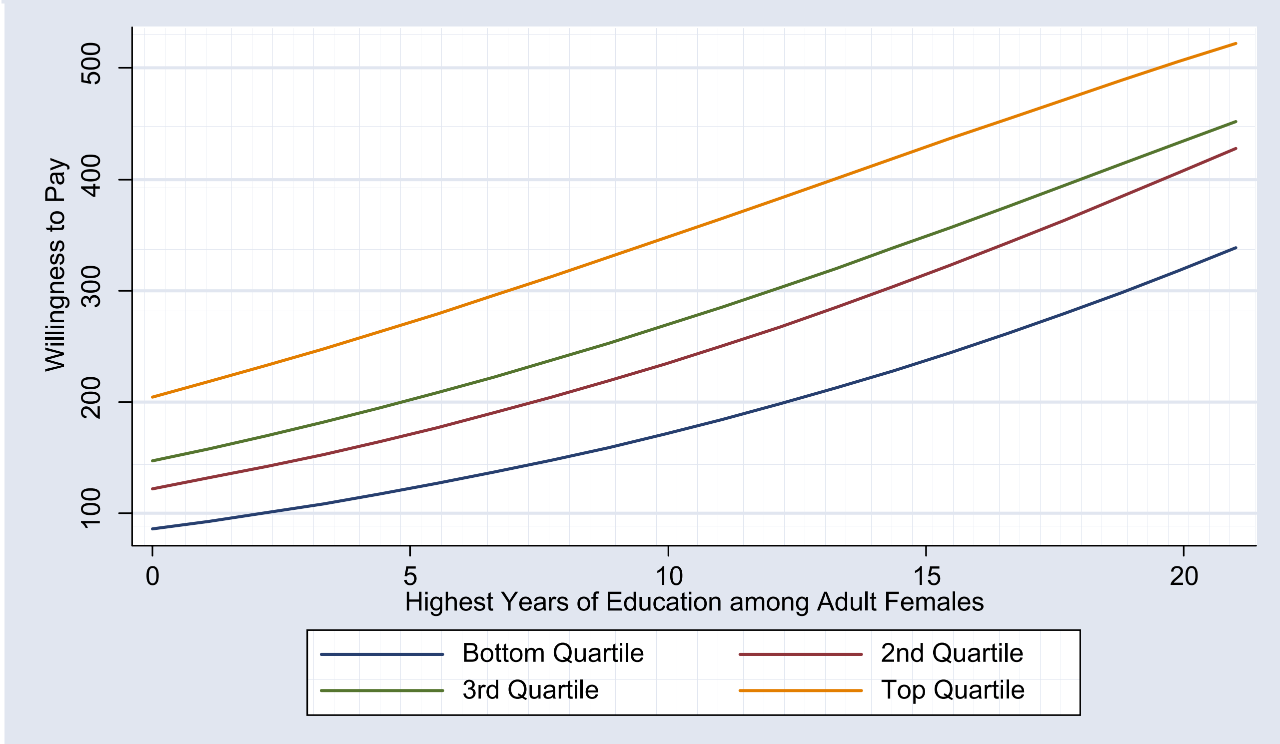



Figure 4



## Figure 5: Wealth and female education effects on WTP




## Figure 6: Wealth and male education effects on WTP