Risk Perception and Altruistic Averting Behavior:

Removing Arsenic in Drinking Water

Yongxia Cai, W. Douglass Shaw and Ximing Wu

Department of Agricultural Economics

Texas A&M University

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Yongxia Cai, W. Douglass Shaw, and Ximing Wu[1]

In this paper we use elicited subjective mortality risks of arsenic in conjunction with sample data on drinking water treatment expenditures to model household averting behavior that may involve motives to protect children. We use a data set for households within selected arsenic hot spots in the United States. To our knowledge, so far, while arsenic has been studied in other countries, few data sets within the U.S. exist that allow a detailed examination of preferences and subjective risks relating to arsenic contamination. A key element of the research here involves exploration of possible altruistic behavior, in protecting children from arsenic risks.

When consumed over a long period of time, arsenic has been shown to increase the risks of bladder and lung cancer at levels of 50 parts per billion (ppb) and above (Smith et al. 1992; Smith et al. 2002). Arsenic may have several other health effects such as skin cancer, but we focus on the major ones here. Baseline risk of dying from lung or bladder cancer for the average person in the United States is approximately 60 per 100,000 people. The risk of getting lung or bladder cancer from drinking water with 50 ppb levels for a period of about 15 to 20 years for a similar U.S. population is estimated to be about 1000 out of 100,000 people. The latency period

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[1]Yongxia Cai is PhD candidate, W. Douglass Shaw and Ximing Wu are professor and assistant professor respectively, at the Department of Agricultural Economics in Texas A&M University.

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we assume to relate to this modeling is communicated to people in the sample to be about 20 years.[2]

Average arsenic-related risks increase to approximately 2000 out of 100,000 people, for a smoker, who already faces a heightened risk of getting and dying from lung cancer. While there is no reliable data to confirm this, the National Research Council (NRC) agreed that because of the larger amount of water consumed per pound of body weight, children may be exposed to an even greater mortality risk for the arsenic in the drinking water (National Research Council, 2001). Most scientists agree that at the very least, children will have a shorter time between the initial ingestion of arsenic and the incidence of possible diseases than adults will face.

Correspondingly, the U.S. federal regulatory standards for arsenic in drinking water (relating to the Safe Drinking Water Act) were tightened from 50 ppb to 10 ppb since January 2001, with compliance to be achieved by January 2006. Because of the lack of precise objective assessments of mortality risks and uncertainty relating to exposures, this standard is controversial. Some scientists believe that the 10 ppb is too low and that the economic cost of meeting the existing rule is therefore too high. Other scientists believe that 10 ppb is not low enough to reduce the risks to safe levels for drinking water. According to Environmental Protection Agency (EPA), the annual economic cost is $205.6 million, while monetized bladder and lung cancer health benefits range from $139.6 million to $197.7 million (EPA, 2000). In addition, there are a large number of other important health-related benefits associated with arsenic reduction, which cannot be monetized.

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[2] As a coincidence a 20 year latency period was considered for chronic, degenerative disease by Hammitt and Liu (2004).

Because of these uncertainties in the known science, it is important to incorporate perceived risks into our modeling of drinking water treatment. We develop a simple risk model to examine household respondents' perceived mortality risk for both themselves and one of their children, if any are present in the household. Next, we investigate whether the household respondent will take his or her perceived risks into consideration while deciding whether to effectively treat their water to reduce mortality risks. The averting behavior model allows examination of whether households with children will exhibit more averting behavior activities, and possibly have greater averting expenditures than households without children. We estimate the risk equations first, and then use predicted values from that in a two-stage Heckman model of observed water treatment expenditures, conditioned on the decision to treat water. For purpose of comparison, we also estimate a simple Tobit model of treatment expenditures. To preview our key finding: we do find some evidence of altruistic behavior, in that a variable that relates to the parent's subjective estimate of the child's risk is positive and significant in the expenditure equation.

The remainder of this manuscript is laid out as follows. First, we provide a basic background on or review of the role of subjective or perceived risks and also on averting behavior studies that relate to environmental risks. Next, we present theoretical models that lead to the estimable models. The survey and the data are described in the next section, along with the estimating equations and their specification. The empirical results follow the specification descriptions and we offer a short summary and conclusions in the final section.

Background Literature

In this section we first review some background literature on the role that subjective or perceived risks take in models that involve decisions in the context of risk or uncertainty, and second, review some studies that previously investigate averting behavior. We also review a few key studies that examine the presence of altruistic behavior in the context of averting behavior models. There has been a very large amount of literature in the fields of economics and psychology or decision theory, both old and new, that considers subjective and perceived risks, and it is impossible to cover it all, so we try to highlight the most relevant papers to what we do in the analysis.[3]

Subjective or Perceived Risks

Traditionally, economic modeling of behavior that involves risks has relied on risks as specified by scientists or so-called experts. However, the designation of experts has itself been called into question (see Rowe and Wright 2001), and many believe that an individual's subjective or perceived risks are likely to better explain an individual's behavior than science-based risks (e.g. Slovic 1987). Because of uncertainties about the nature and quantification of arsenic-related mortality risks, we think those doubts are warranted here. Models based entirely on expert or objective risks will most likely fail to accurately predict drinking water behaviors. First, laboratory experiments have often indicated that individuals tend to underestimate high-risk events and overestimate small-risk events, and their perceived risks are often strongly different from those based on scientific studies (see references in Shaw and Woodward 2008). Previous, but recent research on drinking water behavior in the U.S. may suggest that subjective risks or at least subjective measures of "safety" related to arsenic (Shaw, Walker and Benson 2005) or other contaminants (Poe and Bishop 1999) are likely to be very important.

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[3] The United States Environmental Protection Agency has made a concerted effort at several points in time to fund studies of various health and environmental risks. Several studies emerged in the 1980's that investigated perceived risks, too numerous to cite here, but include the risk perception studies by Paul Slovic and various colleagues of his, David Brookshire, V. Kerry Smith, Ann Fisher, Reed Johnson, Bill Desvousges, William Schulze, Shelby Gerking, Mark Dickie, W. Kip Viscusi, and various other environmental economists.

Perceived risks have been explored for natural hazards (e.g. Bernknopf, Brookshire and Thayer 1990) and a variety of other events. A person's reported subjective or perceived risk is perhaps formed in a manner consistent with a Bayesian learning process. Whether people update risks is an empirical issue, but as suggested in prospective reference theory and elsewhere (see Viscusi, 1989), a Bayesian learning framework involves a weighted average of an individual's prior belief of the risks, plus new risk information he has received to update this prior, as well as the individual's measured behavior and past experiences. The existence of a Bayesian learning process can be consistent with the finding that individuals tend to underestimate high-risk events and overestimate small-risk events, but there is no a priori reason that individuals have to sense that risks are lower than experts do (e.g. Viscusi 1990, finds that cigarette smokers over-estimate smoking-related risks). Liu and Hsieh (1995), Lundborg and Lindgren (2004) used a Bayesian learning process in their estimation of people's smoking risk perception and found out that both smokers and non-smokers overestimated the risks of lung cancer. In their study individuals with higher perceived risks were less likely to be smokers but risk beliefs had no effect on the number of cigarettes consumed by the smokers.

Several other environmental topics that have been addressed include radon (Smith and Desvousges 1989), the value of safety (McDaniel, Kamet and Fisher 1992), and several key contaminants in drinking water. In more closely related work to this paper, Poe and Bishop (1999) examine the relationship between a sample member's ground or well water nitrate level and a proxy for risk, which are couched as response categories (e.g. my well water is definitely safe, probably not safe, etc.). Other possible explanations of discrepancies between subjective and science-based risks usually relate to other types of probability weighting schemes (see Shaw and Woodward 2008 for a review).

Altruism

Altruism can be a factor in a parent's decision to allocate resources for the household. Most literature relating to children assume only one decision maker for the household, or at least that the child does not make decisions. They fall within two categories: paternalistic or non-paternalistic altruism. In the former case, parents are assumed to maximize their own utility, but this utility function includes the children's consumption of goods, which are provided by the parent. In the latter, the child's utility becomes an argument of the parent's utility function.

The estimation of altruistic effects on decisions that could reduce the health risk is now fairly widespread in the literature on purchases of market goods (see as just as few of many examples, Dickie and Gerking 2007; Khwaja, Sloan and Chung 2006; Jenkins, Owens and Wiggins 2001; Carlin and Sandy 1991; Viscusi, Magat and Forrest 1988). Through the purchase of safe products the public reveals its preference and valuation for the reductions in risk and the data allow an opportunity for researchers to explore altruistic behavior. The results from Viscusi, Magat and Forrest (1988) suggest a parent's WTP for a child's risk reduction is 50 percent higher than for themselves.

Carlin and Sandy (1991) examined a mother's purchase and use of safety car seats, and estimated the value of a statistical life (VSL) for children to be $0.75 million. Jenkins, Owens and Wiggins (2001) studied the market for bicycle safety helmet and estimated a separate VSL for children and adults. Their result is surprising in that the VSL for adults is higher than for children. Khwaja, Sloan and Chung (2006), examine the effect of marital status and a spouse's health on one's own smoking behavior, where the spouses' health is an argument in an individual's own utility function.

Subjective risks might depend on preferences for the welfare of other people, in addition to one's own, and if risks are mitigated or avoided, behavior will be related. Values for risk reductions thus might also depend on others' preferences or at least something about the other person, suggesting a form of altruism. The notion that people have preferences and values that are related to preferences for the safety of another person is not new, but credibly estimating such values, or distinguishing portions of values for one's own safety, versus someone else's safety, are new efforts. Liu et al. (2000) consider a contingent valuation approach where mothers are asked about their own protection against minor illness (a cold), as well as their children's. They find that the maximum WTP to prevent comparable illness is twice as large for the child as for the mothers in their sample. Though it is implied, these authors present no formal derivation of a model (one that is utility theoretic) that specifically accounts for the child's welfare within the mother's utility function.

A little more recently, Riddel and Shaw (2003) developed and estimated a formal model of bequest value that decomposes the total value of a risk reduction into that portion of value attributable to one's own protection against risks, and for others. Specifically, they consider both current and future generations' values to accept risks. The model's decomposition allows recovery of bequest values.

Even more recently, Dickie and Gerking (2007) test the hypothesis that an altruistic parent's marginal rate of substitution between an environmental health risk to the parent and to their child is equal to the ratio of marginal risk reduction costs. Their empirical work, in the context of willingness to pay for sun lotions that may reduce the risks of skin cancer (and conditional mortality), supports this prediction. Their theoretical model is a standard utility maximization framework, where the household production model incorporates altruism of parents toward their young children in the context of latent health risks. This appears to be in contrast to the standard risk framework of the expected utility model, but it may be quite consistent with it. The authors estimate a marginal WTP that is perhaps somewhat different from a welfare measure that would arise from formal derivation via the EUM (i.e. an ex ante WTP such as an option price), but this is not discussed in their paper, nor is it here.[4]

Averting Behavior[5]

Averting behavior or self protection is involved when people respond to increased degradation of environmental qualities (Smith and Desvousges 1986) or to the presence of environmental or health risk that may cause harm. For example, people move or reduce physical activities when air pollution becomes intolerable, they apply sunscreen to protect their skins from UV radiation, and they buy bottled water if they suspect that water supplies are polluted. Averting behavior or self protection is a critical factor in the analysis of public risk mitigation policy. Previous theoretical work on averting expenditures has concluded that these expenditures can provide a conservative estimate of the true cost of increased degradation of environmental qualities.[6]

When risks exist that can be avoided by taking some averting or self-protecting action, then the risks are possibly endogenous to the individual. For example, while the risks from drinking water with arsenic levels at 100 parts-per billion are a given, the risks to a household with a raw water supply, but which avoids the raw water supply by treating, are not. Shogren and

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[4] See Jindapon and Shaw (forthcoming, 2008) for a discussion of differences in WTP measures in different risk frameworks.
[5] Related to averting behavior is the “planned” or ex ante expenditure, but discussion of this is postponed until a later section of the paper.
[6] Courant and Porter (1981) demonstrated that if personal environmental quality decreases with increases in pollution and pollution does not directly enter into the utility function, averting expenditures are a lower bound to willingness to pay. In a two-outcome model (Berger *et al (1987))* or *a* non-stochastic model (Bartik (1988)), willingness to pay for risk-reduction may be expressed in terms of the marginal rate of technical substitution between exogenous risk-reduction and self-protection.

Crocker (1991) point out when self-protection influences either the probability of an given adverse outcome, or the severity of health outcomes, or both, the individual's marginal willingness to pay for reduced risk cannot be expressed solely in terms of the marginal rate of technical substitution between ambient hazard concentrations and self-protection.[7]

Averting Behavior and Drinking Water

In the context of drinking water there have been many discussions of averting behaviors such as water treatment, or purchases of bottled water, or boiling contaminated water. Most drinking water studies (Abdalla, Roach and Epp 1992; Collins and Steinbeck 1993; Laughland et al. 1993; Whitehead, Hoban and Van Houtven 1998) do not specifically incorporate a conventional measure of risk or more importantly, perceived risks. Estimates of average monthly expenditures to avoid contamination range from less than a dollar, to over $100 per month (Collins and Steinbeck 1993). Poe and Bishop (1999) examine health issues relating to nitrates in drinking water, and while they have estimates of concentrations, they do not use conventional risk measures relating to them. Instead they attempt to transform "safety" perceptions about the concentrations into a proxy for risk.

Abrahams, Hubbell, and Jordan (2000) estimate a model of several averting behaviors in response to water contamination risks for Georgia residents. Their model examines the choice between using bottled water, water filtered from the tap, and unfiltered tap water. Non-health related water quality effects (taste, odor, and appearance) are incorporated into the model to account for the joint production of utility and health. Their results indicate that the perceived health risks from tap water, the individual's concerns about taste, odor, and appearance of tap

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[7] Quiggin (1992) presents two necessary conditions, not considered by Shogren and Crocker (1991), under which the results of Berger *et al* (1987) may be extended to the general case.

water, and the individual's race and age are the important determinants of bottled water selection. Information regarding current or prior problems with tap water, perceived risks from drinking tap water, and income are the most important determinants of the water filter option. When quality differences between bottled water and filtered water versus tap water are adjusted for, the authors think that averting cost estimates using bottled water expenditures lead to an overstatement of avoidance costs by about 12%. They conclude that averting costs for filtration represent the true cost of averting expenditures.

In a similar study to the one in the current paper, Shaw, Walker and Benson (2005) also model the decision to treat water in the presence of arsenic. However, they actually use the estimated probability of treatment as a proxy for risk, as they have no information on the sample respondent's sense of risk. In summary, though there have been several averting behavior studies relating to water quality, in most of these research studies, the authors fail to quantify the perceived risks. In the next section we lay out a risk model that allows determination of the factors that explain subjective risks, and then link these to a model of water treatment.

The Theoretical Models

In this section we first provide a brief model of risk perceptions, and second, lay out a utility-theoretic water treatment decision model that is linked to the risk model.

Modeling Risk Perceptions

As in a Bayesian learning process about risks proposed in many other studies, the individuals in our sample (described below) might be assumed to have three sources of information that relate to their own risks, as well as to their perceived risks for their children, if children are present in the household. As noted in the introduction, young children may at higher risks from arsenic exposure in the drinking water because of higher arsenic/weight ratios, though to our knowledge, this has not been conclusively demonstrated scientifically for obvious reasons. These three sources are the individual's prior sense of arsenic risks (*P*), the information (*Q*) they receive to update their risks (here, the information that we give them via a mailed information brochure) and the individual's information that relates to behaviors and experiences, as well as his or her personal characteristics, deemed (*R*). With different weights on each term, this can be written as:

$$(1) \qquad \pi = \omega_1 P + \omega_2 Q + \omega_3 R$$

where the weights ω_1, ω_2 and ω_3 capture the individual's evaluation of the relative importance of each source of risk. It is quite possible that everyone weights the information differently from others, so the weights may be individual-specific.

Like most researchers, we have no information regarding the individual's prior sense of risks. We did not ask individuals in the survey sample their prior in advance of giving them information, though for some people, they may not update their prior much based on information they received during the survey process. Viscusi and other risk researchers (e.g. Liu and Hsieh 1995) frequently attempt to model elicited subjective risks using data on these sources of information, but like us, most often do not have knowledge of the individual's prior. In those cases the authors assume that a constant term in the estimation of a model of subjective risks captures the individual's prior risks.

We discuss the risk information communicated to the individuals in more detail below, but this information is basically our presentation of what scientists believe to be true about mortality risks for average people in the population. The presentation is in an information brochure sent to sample households. Since everyone in the sample receives the same information, presuming that they did read the brochure, then there is no variation across individuals and so this new information may influence their prior (via the constant term), but each individual might weight this information differently.

We also told respondents that risks do likely vary across individuals, for a variety of important possible reasons. In keeping with this is the third source of information (R in equation (1)). As examples, an individual's age, gender, education, race, smoke, baseline health status and family health history, may affect her perception of risks. Several studies have found that men tend to judge risks to be smaller than women (Slovic 1999). A person who smokes may form higher risk perceptions based on knowledge of the observed health effects of her smoking. Individuals in poor health may believe they face higher mortality risks than others do, because they are more vulnerable than healthy people.

Finally, some individuals care more about drinking water quality and safety and spend money on water treatment or purchasing bottled water than others do. These attitudes and behaviors will obviously affect the individual's arsenic risk perception: a household that already treats their water to effectively eliminate arsenic risks should report very low or no mortality risks from arsenic, at a water source after treatment. The third source of information we consider consists of individuals' attitudes and behavior, which will be related to water treatment decisions and expenditures. This is a good reason why a household's water treatment decision or expenditure becomes an endogenous variable in forming perceived risk.

As noted above, it is possible that an individual will completely discount Q, and will behave in a manner so as to negate the importance of R, so what is observed in their reported subjective risk is something quite close to their prior, P. Weights will relate to the precision about the risk. As will be seen below, in the survey for this study, after respondents stated their own perceived risk π^p , they were asked to evaluate and report their youngest child's arsenic risk π^c, so in what follows we will estimate two risk equations like equation (1) based on the Bayesian learning process. However, we will not assume them to be identical equations in arguments or the set of explanatory variables. Next, we discuss the water treatment equations we estimate.

The Water Treatment Expenditure Function

In the conventional world of certainty, and with continuous variables of interest, an optimal expenditure function (C^*) for the goods consumed can naturally be derived using duality theory. It provides the optimal amount of ex-post expenditure, given a level of utility for the individual or household. All outcomes are known in the ex-post world. Many researchers (e.g. Jakus 1994) have showed that observed defensive expenditures can, in theory, be expressed as the difference between two restricted expenditure functions, each with different utility levels that correspond to levels of averting behavior that work to make a person better off.

Under conditions of risk, we argue, as have several others, that the appropriate framework is an ex ante one, i.e. behaviors and values for risk reductions are best examined before risky outcomes are known. One ex ante approach then is to consider the probability of engaging in averting behavior, and the role played by averting costs in this framework. This is the approach taken by Åkerman, Johnson and Bergman (1991) in their study of mitigation against radon risks.[8] We take a different approach than theirs, using the planned expenditure function.

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[8] Interestingly, these authors of the radon study mention risks. Their framework should be more or less be a state-dependent expected utility (EU) framework. In the EU framework the appropriate "WTP" is an option price,

Smith (1987) and Smith and Desvousges (1988) expand the basic derivation of the expenditure function under certainty to allow for the presence of risks, leading to the ex ante or planned expenditure function, (C_p^*) .[9] Here, the key point is that when a purchase is made, outcomes are not known. Expenditures are made to hold expected utility (EU), not certain utility, at a given level. For example, in our study household members purchase water treatment, but they do not know if they will someday get sick and die from lung or bladder cancer. The resulting planned expenditure function will be:

(2) $$C_p^* = C(Y, EU)$$

We return to discussion of the planned observed expenditure function below. Here, note that in (2) since EU involves the all the things that can be used to specify the expected utility function, including the probabilities that weight the outcomes, then planned expenditures will also involve them. To our knowledge, though Jakus (1994) and others have estimated an empirical version of C* based on duality theory, no one has estimated a model of (C_p^*) . Most empirical models of observed expenditures, such as the one Jakus estimates, use the Tobit procedure because only those who make an expenditure report positive (non-zero) amounts of expenditure. All others in samples report no expenditures. However, underlying the reported or no expenditure in our case, is the decision to treat water in the first place.

Modeling the Decision to Treat Water

We assume that if the technical water treatment approach taken successfully removes arsenic from water, the objective additional mortality risk related to arsenic will fall to zero. This is true

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however, it is not clear how an OP measure relates to the authors' use of engineering costs, converted to annualized values. It is interesting that the study uses revealed preference, not stated preference data.

[9] The idea of an ex ante expenditure function was also developed by Simmons (1984).

for many types of water treatment devices, but not for simple water filters, such as the charcoal filters on refrigerators. Our respondents are told this fact. Given limited information and data the parent's treatment response to her own risk and her child's risk may be considered as discrete choice decision (treat versus do not treat). Let V^0 be the parent's indirect expected utility if she decides not to treat water. With no treatment the parent perceives that the entire household faces arsenic mortality risk from drinking water, but that it could be different for the parent π_{nt}^p and child π_{nt}^c. Suppose V^0 takes the following simple linear form:

$$V^0 = U(Y, \pi_{nt}{}^p, \pi_{nt}{}^c) = \alpha^0 Y - \beta_1 \pi_{nt}{}^p - \beta_2 \pi_{nt}{}^c + \gamma^0 Z + \varepsilon^0 \tag{3}$$

where Z is a vector of personal attributes such as age, gender, education, and awareness of arsenic risk, and ε^0 are the usual unobservable factors.[10]

Let V^1 be the indirect utility if the parent decides to treat water at an exogenous treatment cost *TC* incurred by the household, with expectation that the parent's perceived mortality risk for both herself and the child are reduced. Correspondingly, we let V^1 be:

$$V^1 = U(Y \;, \pi_t{}^p, \pi_t{}^c) = \alpha^1 (Y - TC) - \beta_1 \pi_t{}^p - \beta_2 \pi_t{}^c + \gamma^1 Z + \varepsilon^1 \tag{4}$$

Again, ε^1 are the usual unobservables. Note that the term, TC, in equation (4) should not be confused with observed chosen expenditures on treatment, which are an endogenous variable (exogenous price times a chosen quantity of treatment).[11] In (3) and (4) the marginal utility of

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[10] While the probabilities are typically terms that are expressed as weights "outside" the deterministic utility function in theoretical presentations of the EU framework, the resulting conditional indirect expected utility function may take such a simple form as in (2), depending on the distribution of the risky outcomes. See Riddel and Shaw (2006) for an example derivation, though theirs is not a conventional EU framework.

[11] It appears to us that some authors have confused this in their utility-theoretic model, or at least in their presentation of it. However, note that as in the "travel cost" model of recreation demand, where the random utility framework is often used, the conditional indirect utility function involves a unit of the good consumed and a "price" per unit. In the recreation setting the proxy for the unobserved unit (trip) price is the travel cost. In our setting the

risks are assumed to be the same, while the constant marginal utility of income (as it is linear in (3) and (4)) and utility from personal attributes are assumed to be different depending on the choice to treat.

Treating water will be the optimal choice if the individual's conditional expected utility of treating, V^1, exceeds the conditional expected utility from not treating. Subtracting (3) from equation (4) gives the usual utility difference:

$$
\begin{aligned}
V^1 - V^0 = \; & [(\alpha^1 - \alpha^0)Y - \alpha^1 TC] + \beta_1(\pi_{nt}{}^p - \pi_t{}^p) \\
& + \beta_2(\pi_{nt}{}^c - \pi_t{}^c) + (\gamma^1 - \gamma^0)Z + (\varepsilon^1 - \varepsilon^0) \qquad (5) \\
= \; & (\alpha Y - \alpha^1 TC) + \beta_1(\pi_{nt}{}^p - \pi_t{}^p) + \beta_2(\pi_{nt}{}^c - \pi_t{}^c) + \gamma Z + \varepsilon
\end{aligned}
$$

Here, in the last line of (5), we let $\alpha = \alpha^1 - \alpha^0$, $\gamma = \gamma^1 - \gamma^0$ and $\varepsilon = \varepsilon^1 - \varepsilon^0$. The first term $(\alpha Y - \alpha^1 TC)$ in (5) is the net utility loss from income because of water treatment. Risk differences are important here: the second term, $\beta_1(\pi_{nt}{}^p - \pi_t{}^p)$ indicates the utility gain from a risk reduction for the parent, while the third term $\beta_2(\pi_{nt}{}^c - \pi_t{}^c)$ represents the net utility gain to the parent from the risk reduction for the children. Simply stated, equation (5) implies that the individual will decide to treat water if their perceived ex ante net benefits from the risk reductions exceed the perceived marginal costs (their income loss from the water treatment costs they make).

The Relationship between Water Treatment Decision and Planned Expenditures

Obviously the decision to treat water and the planned expenditure function are related. An individual who decides not to treat their households' water also plans to spend nothing on

proxy for the unobserved price per unit of water treatment is the cost of treatment. This may vary across households the same way that travel costs vary across individuals who make trips. I.E. the cost of a treatment system may differ in different geographical regions, or by type and quality of the treatment system purchased.

treatment, while one who decides to treat must spend on it. What we assume is that the treatment decision is made in the context of risk. Once that is made, the expenditures are conditional. We mentioned that the usual approach in estimating an equation using observed averting expenditures assumes that the equation is based on the certainty-based minimization of expenditures, subject to holding certain utility constant, but that in estimation, the Tobit equation is used in recognition of possible censoring at zero for those who do not treat. By considering the expected utility framework above, we can explicitly link the decision to treat in the face of risk with observed expenditures. We do this empirically, by using the usual Heckman procedure. Observed expenditures for our households are thus conditioned on the decision to treat, which in turn depend on their perceived risks.

The survey, Sample and the Data

The data used to estimate the models came from a survey conducted during late 2006 and early 2007 (see Shaw, et al. 2006 for a more complete description). The survey was conducted in Albuquerque (New Mexico), Fernley (Nevada), Oklahoma City (Oklahoma), and in two areas within Outagamie County (Wisconsin). These targeted areas were chosen because each had potential households who are drinking water that may have arsenic levels that exceed the 10 ppb standard; they are not meant to represent any household in the United States, rather, the sample should be representative of households in areas where the standard is exceeded in drinking water supplies. The sample contains both households who get their water from public drinking water suppliers, and those on private wells, which are not regulated by the federal government.

Prior to conducting the full survey, focus groups were conducted to assist in design of the survey instrument. During that process researchers learned that drinking water behaviors were more complicated than initially thought, and that the focus group respondents were more comfortable with a presentation of risks using a risk ladder than they were with a risk grid, which is an alternative risk-communication device. The responses also led to a different final survey plan than initially envisioned. Other details about the focus groups and what was learned during them are provided in Shaw et al. (2006).

To implement the final survey, a phone-mail-phone strategy was used. The initial sample was randomly recruited by telephone (for existing listings of phone numbers). Those who participated in this first call were at first not given much information about the study, and were then given a screen survey. During this call we collected information on respondents' source of drinking water, their level of concern for negative health effects from poor air or water quality, their concerns related to their drinking water, their tap water use, and several demographic variables such as age, income, education, gender, and home ownership. 733 households completed the screener survey. At the end of this survey, all screener participants were asked if they were willing to participate in a follow-up survey. 565 respondents stated that they would do so. By answering questions in the screen survey, the respondent no doubt could discern the topic of the study had to do with water quality, and possibly, with arsenic issues in their drinking water.

Respondents willing to participate in the remainder of the study were sent an information brochure by mail, that included general information on arsenic and questions regarding respondents' households' current and historical health status, uses of tap water, choices of water treatment, water treatment expenditure, and perceptions of the health risks from arsenic in their drinking water. Though 565 individuals who did the screener survey had stated that they would participate, only 353 households actually completed the follow-up survey, yielding an adjusted response rate of about 48% of the original 733 who completed the screener survey.

This response rate, while somewhat low, is reasonable given the complexity of the topic, and the fact that there were two more parts to be involved with. Participating respondents were directed in the mail brochure to complete several questions. Most critical for the collection of risk-related data was for them to make marks on risk ladders in the brochure to indicate their perceived level of mortality risk associated with exposure to arsenic in their tap water, and they were told that they would then be contacted for their answers, by telephone.

The final step in the survey process was the follow-up phone call which followed the initial screener phone call within ten days. The telephone survey allowed for interaction between the respondent and the trained telephone interviewer, in that there was confusion regarding the assessment of risks, or the respondent had questions about the mailed brochure information. During this final phone survey, we obtained the answers to the questions posed in the mailed brochure on tap water use, water treatment choice and the reasons for that, arsenic risk perceptions, health status, and other information.

Possible Sample Selection Effects

Because only 353 of the original 733 respondents actually participated in the complete study, this reasons a concern about possible sample selection bias for the final and estimating samples. A nice feature of the phone-mail-phone format is that it allows examination of differences between the original sample of 733, and only those who cooperated to participate in the complete study. The usual thoughts related to survey sample bias fall into two categories. The first is that only people with certain demographic characteristics will participate. For example, it is often thought that people with higher incomes are busier than people with lower incomes (they have a higher opportunity cost of time) and thus opt out of surveys. The second category of concern relates to the salience of the topic for participants: only those who are really concerned or interested in the topic will participate, and this group thus likely has a biased set of preferences. We compared key demographic characteristics of both the original and final samples, as well as a response to a question about the importance of water quality. There are no statistically significant differences that can be observed between the two samples. We also ran probit models of both intended and actual participation in the study on the full sample of 733 respondents, controlling for all of the variables for which we have data from the first phone survey. More results are fully reported elsewhere, but there are few variables that are significant in explaining participation.[12] Being male and thinking environmental or water quality both have positive and significant effects on participating in the final study, but as the above states, there are no important differences in the composition of the original and final samples in those dimensions.

Table 1 shows the variables definitions and their descriptive statistics used in this estimating sample for this study. The majority of the variables in this study relate to water treatment decisions, but other variables used in modeling are not always available for each respondent because of item non-response on the part of some of the members of the final sample of 353. The final usable estimating sample is therefore 247 respondents. The respondents indicated their arsenic treatment devices if one was obtained, and their annual treatment expenditures, and their reasons for treating their water. On average, the 353 respondents reported spending $55 per year on water treatment, which is comparable with the available information on replacement of filters in reverse osmosis systems capable of removing arsenic. However, two respondents with treatment expenditure $1000 and $3648 are excluded from the estimation

[12] Tables of these results are available upon request of the authors. The probit model on the full sample correctly predicts 55% of participation decisions, slightly better than the 50% percent of random predication. The Brier score for the estimated probit model, which is a recommended alternative measure of fit, was .247, quite close to the score (0.25) that indicates a forecast of a binary event at 50/50 (see Jin and Bessler 2008). These results indicate little self selection (conditional on observables) in people's participation decision in our sample.

because these high amounts were thought to be outliers. These were probably capital-related expenses, while other amounts were typically maintenance-related. For the estimating sample of 247 in Table 1, average expenditures are a little less than the overall sample.

All respondents who participated in the final study were asked about their arsenic mortality risk perception for their drinking water. This risk perception is likely to be a post-treatment risk if they treat water. Depending on the treatment devise they used, the respondent already knew, or learned from our information brochure how effective the treatment devises are in removing arsenic. If people don't treat their water, then their initial (before treatment) perceived risk will be unchanged. Table 2 shows the participants' (used in the estimating sample) mean risk perceptions for themselves and their children, sub-grouped by treatment decision and if children are present in the family. The respondents' mean risk perception for themselves for the full estimating sample is 0.00556. Some households indicate risks as high as 0.04, but 86% of the overall sample indicates that their mortality risks are below than 0.01. Recall that the science-based estimate is about 0.01 for the U.S. population at large, and for levels of arsenic of about 50 ppb.

It appears that most of the respondents in the estimating sample understood the information presented in the risk ladder and other risk information in the mailed brochure. However, on average, the risk perception for respondents with children is significantly higher than the perceived risk for respondents without children. Parents indicate that their water treatment efforts will reduce at least some of risks they face. However, if we only compare the non-parent respondents to the parents, the average perceived risk for those who treat water is actually higher than those who don't treat water.

Table 2 also shows that the average parent's subjective risk for their children is very close to the mean risk for themselves, suggesting that the parent's own risk beliefs will play an important role in formulating the children's risk. The information brochure does suggest that children might face a different risk than adults, but the science couches that in terms of a shorter time until disease can manifest itself rather than as a higher point estimate of risk. Next, an econometric model is used to examine the relationship between the own and children's risk perceptions.

Empirical models/Specification

We have described three equations that will be estimated and linked together for the analysis: (1) respondents' risk perception for themselves; (2) the respondents' risk perception for the youngest child if they have one; (3) and finally, a treatment expenditure decision that will be a function of estimated risks.

We first estimate the perceived risk of those households who did not treat their water, treating this group as the baseline group. We then use estimated parameters from the baseline group to predict the counterfactual pre-treatment risk for those households that treated their water. The difference between the second groups' perceived risk (after treatment) and predicted risk (before treatment) captures the expected risk reduction for those who treated their water. The expected risk reduction for the children is estimated similarly. We then estimate household treatment decisions based on their observed characteristics and expected risk reductions for the adults and for the children (if present). Finally, we estimate household treatment expenditure as a function of household characteristics and expected risk reductions. The censored nature of the treatment expenditure is accounted for by using the Tobit or Heckman two step method. The results from these two approaches are quantitatively very similar.

Risk perceptions for the participants

Theoretically, the decision to treat likely influences the stated risks from each respondent, but this decision is also an endogenous choice variable that has been shown to depend on factors such as income and the price of treatment devices (see Shaw, Walker and Benson, 2005). To avoid the difficulties that would arise in finding valid instrumental variables for modeling endogenous treatment, we separate the sample into two groups: those who treat water are in the first group (j=t), and those who don't report treating their water (j=nt) in the second. We use the risk equation for the nt group to forecast the before-treatment risk for everyone in the sample. We then examine the difference between this predicted before-treatment risk for those who treat, and their stated risk. When the stated risks are lower for this group we interpret this as the risk reduction they perceived due to treatment. Since the nt group doesn't treat their water, the risk difference or reduction is assigned to be 0. In other words, the expected risk reductions for an individual will be:

$$(6) \qquad DiffOwn_{ji} = \begin{cases} Risk\hat{O}wn_{ji} - RiskOwn_{ji} & \text{if j = t (treat)} \\ 0 & \text{if j = nt (do not treat)} \end{cases}$$

In the survey, the respondents can give either point estimate of his risk if he is sure, or an interval if he is not very uncertain about a point estimate for his or her household. For the second case, the mid-point of the stated interval is used.[13] As described in our conceptual framework, risk perceptions can, in theory, be expressed as a weighted average of three sources of information. The individual's prior sense of risk is assumed to be captured in a constant term that is estimated for all individuals. Gender, education, age, smoking status, number of children

[13] In contrast, some researchers estimate an interval model that can then be used to predict risks for both those who state a point estimate, and those who provide an interval.

in the family, health status of own and other family members, the respondent's job increases the risks of getting bladder cancer (some occupations do), and his or her safety perception about drinking water are included as variables in the model of perceived subjective risks.

Since the subjective risk is bounded between 0 and 1, the log odds transformation for subjective risk was regressed on the explanatory variables using Generalized Least Squares (GLS) to model the respondents' perceived risk for themselves and their children, when present, for a second subsample that household's water is not treated. This approach has one advantage over other possible modeling approaches, which is to ensure that the predicted subjective risk remain within the range of 0 and 1[14]. In addition, we recognize that in the risk modeling itself, sub-samples may self-select to treat their water or not to treat water, so a Heckman two-step method was also conducted here to account for the possible selection (those who self-select into water treatment) bias in the cost model. The coefficient for the inverse Mills ratio was not statistically significant, suggesting little sample selection bias so a simple log odds transformation is viewed to be appropriate.

Risk perceptions for the children

In the survey parents also are asked to assess risks for their youngest child. Because the decision to treat is an endogenous choice variable, we adopt the same procedure as above, and forecast before-treatment risks for the treatment group to be able to extract the difference, arriving at the similar equation to (6), for children's risk reduction. As we can see in Table 2, the respondent's risk perception for herself is very close to the subjective risk perception for her child. We hypothesize that there are some unobserved variables that may influence both the parent's risk

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[14] Alternatively, some use the beta distribution to model reported probabilities, but this distribution is often unwieldy in estimation.

perception for herself and her child. Therefore, the parent's own perceived risk is included as an explanatory variable in the model to proxy these unobserved factors.

Treatment Decision/Expenditure decision

We assume that the treatment decision may depend on the type of water system the household is on (public or private), their gender, and whether they say they are using their tap water for all of their water needs. The treatment equation, as well as the expenditure function, is also a function of expected own and children's risk reductions. Our test of behavior consistent with altruism depends on whether and which of the risk difference coefficients are significant. If only the parent's own risk is significant, then the household member makes decisions solely based on those risk reductions and does not seem to be concerned about the children. Otherwise, they care about the child, or both.

We also implicitly map from the utility function to the expenditure function, including variables that may affect expected utility such as education, whether the respondent owns their home, and whether the respondent is a current smoker. We also include two variables representing attitudes towards arsenic risk (*Arsenicnfor*: whether they had much arsenic information prior to our survey, and *Safety*: their strength of their health concerns about the drinking water), and two variables explaining the reasons for treating their water (improve the taste and smell).

Empirical Results

Own Risk perceptions

We had no initial thought that subjective risks of arsenic would be higher than the best estimates of scientists, which again is about one in one hundred, or 0.01, for the average non-smoker, nor did we think it would necessarily be lower. This is an empirical issue. Table 3 presents the log odds transformation model for subjective own and children's arsenic risks separately. In the own risk model, status such as a current smoker, and the number of children in the household have positive and significant effects (at 1% or the 5% significance level) on own subjective risk, while the coefficient on the variable *Safety* (a rating of the respondent's general perceptions of the safety of drinking (tap) water) is significant and negative. *Education* is negative and weakly significant (at about the 8% significant level). No other included variables are significantly different from zero in the model of the parent's own risk for this sample. The marginal effects of each variable are in the fourth column of Table 3, and these are considered next.

The effect of *Cursmoke* (being a current smoker = 1, = 0 otherwise) on stated arsenic-related risks is interesting, but not should be confused with such estimates in the smoking literature because those generally relate specifically to mortality from lung cancer as it relates to smoking behaviors. Recall that ingesting arsenic may increase the risks of dying from at least two diseases (lung and bladder cancer), though if detected early, bladder cancer may not lead to death (see references and more discussion in Shaw et al. 2006). Also recall that the scientist's best estimate of arsenic mortality risks for a non-smoker who consumes water with about 50 ppb of arsenic in it for a period of about 15 to 20 years is one in a hundred, or 0.01. The risk ladder included in the information brochure not only showed this, but also showed that the risks for a smoker are approximately twice this large as for a non-smoker. The marginal effect of the dummy variable indicating current smoking is around 0.00554, indicating that smokers understood the information from the risk ladder to some extent. An average smoker has a perceived arsenic mortality risk that is 0.00554 higher than a non-smoker, ceteris paribus.

The number of children in the family carries a positive and significant sign (at 1% significance level). For households with one child, as compared to none, the stated or subjective risk will increase by around 0.00094. People who state, on the scale of agreement with the statement that tap water is safe, that they more strongly agree by one unit, this decreases the marginal subjective risk by 0.00134.

It is often thought that education is important in communicating risks to people, and that more educated people better understand information given to them. Our prior on this coefficient was that an individual with higher education will obtain more knowledge from public risk information (Liu and Hsieh, 1995) and form a reasonable subjective estimate, but in our empirical model more education lowers the risk estimate by 0.0014. Finally we note that while all of the other variables are statistically insignificant at even the 10% level, most of the signs do make sense.

Subjective Risk perceptions for children

The subjective risk perception model results for children for the second group are also shown in Table 3. The parent's predicted own risk (*RiskOwn*) plays a dominant and significant role in determining the risk perception for the child. The coefficient is significantly greater than unity, reflecting the tendency for parents to make higher estimates of risk for their children than they made for themselves. Using the predicted risks for the parent captures the influence of other variables used in the *Riskown* model, so it is not surprising that the other variables are not significant in this model. Note that if the variable *Riskown* is omitted in the model, the effect from the other variables is significantly different than zero, which of course indicates that *Riskown* has a strong correlation with these variables. Next we turn to discuss the results of estimated treatment and averting expenditures.

Estimated Treatment and Averting Expenditures

Table 4 presents the results of our Heckman two step model, where the first step models water treatment decision and the second, treatment expenditure conditional on treatment. We present three slightly different alternative specifications of the treatment and observed expenditures equations (Models 1a, 1b and 1c), and the treatment equation results are in the top half, while the cost equation are in the bottom. Model 1a is the most parsimonious specification, and avoids overlap in variables used in both equations. Note that for Model 1a only, the mills ratio is significantly different from zero. In this simple specification, being a homeowner, having information that arsenic is a problem and having and more concerns about arsenic related to health positively influence the decision to treat. Being on a public system reduces that tendency. The two risk difference variables are each positive, and significantly different from zero in the cost equation, suggesting mixed motives for averting behavior. Interesting, the respondents who say they use the tap as the source for all their drinking water and cooking needs spend less on treatment, though this is weakly significant.

In all the models in Table 4 being a homeowner is very important in the decision to treat, which is not surprising, and households on public water systems are also less likely to treat internally than those on private systems. While it may seem obvious that households connected to public suppliers are more likely to rely on the public supplier to treat and meet water quality standards there is no guarantee that private well users will be willing to bear the added cost and decide to treat. The coefficient for the inverse Mills Ratio, which indicates the importance of the selection variable (water treatment) is not significantly different from zero for all the other specifications (Models 1b and 1c). This is likely because Models 1b and 1c have specifications that include several variables with which the mills ratio is correlated.

The most important component in the results pertains to whether the two risk reduction variables matter in each of the models. If the *Diffkid* variable is significant in either, this is an indication of behavior consistent with altruism. In Models 1b and 1c, note that neither the difference in own risk nor in children's risk is significantly different from zero. However, note that in all specifications for the cost model, corrected for possible treatment effects, both variables are positive and significant at about the 6 or 7% level, or greater. All the specifications support the notion of mixed altruism.

For purposes of comparison with the two-step Heckman approach, we estimated a Tobit model of on the treatment expenditures. The results of three specifications of the Tobit model are reported in Table 5 (2a, 2b, and 2c). Here again, both risk differences variables are significant and positive, at least at the 10% level (Model 2b). Similar influences from the water system, homeowner and arsenic information variable are illustrated in the Tobit specifications. Our results are consistent with those of Dickie and Gerking (2007), who fail to reject the null hypothesis that the marginal rate of substitution of risk reductions between parent and child's risk is equal to one.

Conclusions

Protection of young children from environmental hazards has become a worldwide priority of government policies set to improve human health. Self protection and altruism in families are crucial behavioral factors in determining the effectiveness of these public policies. Other researchers have found evidence that parents are willing to protect their children (Dickie and Gerking 2007), often resulting in values that are higher for child-protection than for themselves (see Liu et al. 2000). In this paper we have developed a two-stage structural model within the random utility framework to model the household's risk averting behavior with respect to arsenic-related mortality risk. We are able to test whether the parent's sense of risk for the child is important in the empirical models.

Our empirical results suggest that parents engage in a form of mixed altruism. Parents do allocate family income to water treatment to reduce the perceived arsenic mortality risk for both the adults in the household and their children. Parents are willing to spend more to make a trade off between their risk and their children's risk. This finding is expected to provide useful information for designing effective government polices to improve human health, especially health for children who may be particularly vulnerable to exposure to toxic substances like arsenic.

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Table 1. Variable Definition and Descriptive Statistics for Estimating Sample

Variables	Definition	Mean	Std. Dev.
RiskOwn	Participant's own subjective risk	0.0056	0.0093
RiskKid	Participant's perceived risk for her youngest child	0.0025	0.0080
Female	=1 if female, 0 otherwise	0.40	0.49
Education	Education level, =1 of college or above, 0 otherwise	0.67	0.47
Ownage	Participant's age	51.75	15.28
Cursmoke	=1 if he is current smoker, 0 otherwise	0.15	0.35
Dkids	=1 if a participant has at least one child, 0 otherwise	0.36	0.48
N_Kids	Number of children in the household	0.67	1.04
Age_K1	The youngest child's age	2.91	5.07
Health_K1	The youngest child's health status, range from 1~5 with 1= Excellent, 5=Poor	0.49	0.76
Healthother	The worst health status of other adult members in the household, range from 1~5 with 1= Excellent, 5=Poor	1.60	2.14
Healthown	The participant's own health status, range from 1~5 with 1= Excellent, 5=Poor	2.20	0.98
Homeowner	=1 if the participant owns a house, 0 otherwise	0.93	0.26
Wasys	Water supply system, 1=Public, 0=Private	0.67	0.47
Riskcareer	=1 if the participant's job is risky, 0 otherwise	0.25	0.43
Arsenicinfor	=1 if the participant knows arsenic problem in the local water supply, 0 otherwise	0.61	0.49
Healconcern	How concerned the health problem caused by arsenic in the drinking water, range from 1~5 with 1=Not at all concerned, 5= Very concerned	3.31	1.43
Safety	Whether the tap water is perfectly safe to drink, range from 1~5 with 1=Strongly disagree, 5=Strongly agree	3.17	1.32
Tap	Do you get all of the water that you use to cook, or make coffee, tea, or juice from your tap? =1 if yes, =0 if no	0.85	0.35
Smell	Use a water treatment device to make it smell better, 1=Mentioned, 0=Not mentioned	0.03	0.18
Taste	Use a water treatment device to improve the taste, 1=Mentioned, 0=Not mentioned	0.10	0.30
Income*	Annual household income, $1000	66.34	34.36
Treat	=1 if water is treated, =0 otherwise	0.44	0.50
Tcost	Annual water treatment cost, $	36.53	70.21

Note: The estimating sample size is 245.

*Missing incomes are predicted by a hedonic regression.

Table 2. Risk Perceptions for the Participant's Self and His/Her Child

	Treatment Decision		Full Sample
	Do not treat	Treat	
RiskOwn			
No children in household			
Mean	0.00449	0.00474	0.00460
StdDev	0.00669	0.00767	0.00711
Sample size	89	69	158
Children in household			
Mean	0.00781	0.00668	0.00730
StdDev	0.01293	0.01125	0.01215
Sample size	48	39	87
Full sample of household			
Mean	0.00565	0.00544	0.00556
StdDev	0.00945	0.00912	0.00929
Sample size	137	108	245
RiskKid			
Mean	0.00749	0.00666	0.00712
StdDev	0.01288	0.01147	0.01221
Sample size	48	39	87

Table 3. Risk Perception Model for Respondents Themselves and Their Children in the Control Group

	Riskown			Riskkid		
	Coef.	P-value	Mar. Effect	Coef.	P-value	Mar. Effect
_Cons	-5.334	0.000		-5.454	0.000	0.00000
Riskown				109.454***	0.000	0.36599
Female	0.007	0.980	0.00003			
Education	-0.343*	0.085	-0.00144			
Ownage	0.005	0.609	0.00002			
Cursmoke	0.975***	0.001	0.00554	-1.234	0.266	-0.00315
Safety	-0.341***	0.000	-0.00134	-0.021	0.766	-0.00007
N_Kids	0.239**	0.022	0.00094	-0.136	0.195	-0.00045
Healthown	0.175	0.154	0.00069			
Healthother	0.101	0.180	0.00040			
Riskcareer	0.053	0.828	0.00021			
Health_k1				-0.169	0.245	-0.00057
Age_k1				-0.031	0.118	-0.0001
N		137			39	
Log pseudolikelihood		-3.696			-1.447	

Note: Asterisk ***, **, and * denote coefficients that are statistically significant al the 1% level, 5% level, and 10% level respectively.

Table 4. Heckman Two Step Model for Averting Behavior in Water Treatment

	Model 1a		Model 1b		Model 1c	
	Coef.	P-value	Coef.	P-value	Coef.	P-value
Treat						
Intercept	-1.855***	0.002	-1.897	0.002	-1.353	0.01
Income	0.000	0.732	0.001	0.64	0.001	0.727
Income*Dkids	0.000	0.899	0.001	0.904	0.000	0.953
Diffown			0.009	0.492	0.009	0.464
Diffkid			0.023	0.122	0.023	0.135
Female			0.208	0.237	0.161	0.356
Homeowner	1.021***	0.012	0.961**	0.019	0.948**	0.019
Wasys	-0.412**	0.026	-0.419**	0.026	-0.479*	0.012
Healconcern	0.113*	0.067	0.102*	0.102	0.082	0.176
Arsenicinfor	0.426***	0.013	0.407**	0.02	0.392**	0.025
Dkids	-0.115	0.801	-0.188	0.688	-0.153	0.744
Tap	0.403	0.110	0.467*	0.072		
Education					0.052	0.781
Cursmoke					-0.122	0.631
Log likelihood	-154.753		-151.761		-153.249	
Likelihood ratio	26.69	0.001	32.68	0.001	29.70	0.003
Tcost						
Intercept	182.231***	0.000	32.023	0.757	28.486	0.806
Income	-0.301	0.205	-0.385	0.105	-0.429*	0.078
Income*Dkids	0.165	0.479	1.100*	0.068	1.080*	0.071
Diffown	1.355**	0.054	1.361*	0.067	1.833**	0.026
Diffkid	2.262***	0.000	2.315***	0	2.480***	0
Homeowner			41.379	0.521	34.432	0.62
Healconcern			6.022	0.279	6.852	0.214
Arsenicinfor			19.459	0.329	24.922	0.217
Dkids			-69.851	0.111	-69.931	0.109
Education					5.409	0.74
Tap	-0.46.493*	0.097				
Cursmoke					-35.901	0.133
Inverse Mills Ratio	-57.843*	0.076	-6.864	0.869	2.706	0.955
Rho	-0.659		-0.092		0.037	
Sigma	87.789		74.584		73.559	

Note: Asterisk ***, **, and * denote coefficients that are statistically significant al the 1% level, 5% level, and 10% level respectively.

Table 5. Tobit Model for Water Treatment Expenditure

	Model 2a		Model 2b		Model 2c		Model 2d	
	Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value
Intercept	-153.377	0.008	-182.554	0.006	-148.844	0.01	-173.440	0.003
Income	-0.252	0.381	-0.245	0.394	-0.283	0.333	-0.222	0.44
Income*Dkids	0.763	0.240	0.775	0.232	0.722	0.266	0.783	0.217
Diffown	1.967*	0.061	2.005*	0.056	2.265**	0.037	2.603***	0.013
Diffkid	3.579***	0.000	3.610***	0.000	3.610***	0.000	3.558***	0.000
Female	16.779	0.336	19.074	0.279	15.142	0.384	22.185	0.196
Homeowner	110.740**	0.015	110.233**	0.016	106.733**	0.018	102.879**	0.024
Wasys	-45.099**	0.017	-41.753**	0.029	-44.211**	0.02	-38.767**	0.042
Healconcern	10.612*	0.082	11.704*	0.060	11.361*	0.064	11.124*	0.064
Arsenicinfor	47.291***	0.009	47.468***	0.009	47.855***	0.008	42.623**	0.017
Dkids	-64.882	0.176	-65.984	0.169	-61.159	0.203	-57.736	0.220
Tap			25.859	0.327				
Education					3.475	0.853	11.027	0.566
Cursmoke					-26.681	0.306	-31.263	0.228
Taste							99.057***	0.000
Smell							85.828**	0.042
Log likelihood	-710.005		-709.514		-709.438		-698.278	
Likelihood ratio	48.95	0	49.93	0	50.08	0	72.40	0
Sigma	112.474		112.404		111.796		107.895	

Note: Asterisk ***, **, and * denote coefficients that are statistically significant al the 1% level, 5% level, and 10% level respectively.