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A General Framework for Estimating Willingness-To-Pay To Avoid Endogenous Environmental Risks[1]

Yoshifumi Konishi[2]
Department of Economics
Williams College

and

Kenji Adachi
Department of Applied Economics
University of Minnesota

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[2]Corresponding author. Department of Economics, Shapiro Hall Rm 327, 24 Hopkins Hall Dr., Williams College, Williamstown, MA 01267. E-mail: yoshifumi.konishi@williams.edu. Tel: 413.597.4766. Fax: 413.597.4045

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ABSTRACT

This paper proposes a general empirical strategy to estimate willingness-to-pay (WTP) for exogenous risk mitigation when environmental risks are endogenous in protective actions and consumers are imperfectly informed about the ambient risk levels. The strategy consists of a set of survey techniques and the dummy endogenous variable model (Heckman, 1978) to control for correlation in unobserved errors that enter the WTP equation and the protection-decision equation. The method is applied to the non-market valuation survey data on arsenic contamination in drinking water. Our results indicate that the estimated WTPs are significantly higher for households without self-protective action. Our approach thus offers not only the correct welfare estimate for exogenous reduction of environmental risks, but also yields policy implications qualitatively much different from the conventional approach. We also apply our method to estimate the welfare value of the policy to inform and educate the public about the arsenic risk simultaneously with public risk mitigation. The estimated welfare value is similar to, though slightly higher than and statistically different from, that of risk mitigation without information component. This occurs due to the competing effects of information dissemination and risk mitigation efforts.

JEL codes: D8, Q51, Q53
Key words: self-protection, environmental risk, compensating variation, dummy endogenous variable

1. Introduction

Information about individual averting behaviors is often used to make inferences about willingness-to-pay (WTP) for health, safety, or environmental quality (e.g. [15] [25] [26] [36] [39] [40]). This approach relies on the earlier theoretical result [7] [13] [24] [46] that the marginal benefit of exogenous pollution reduction equals the cost of self-protection, translated via the marginal rate of technical substitution between pollution reduction and self-protection. Using a continuous-state stochastic model, however, Shogren and Crocker [47] [48] countered this claim, arguing that "unobservable utility terms cannot be eliminated from marginal willingness-to-pay expressions, implying that empirical efforts which identify marginal rates of substitution with willingness-to-pay are misdirected" ([47], p.13).

Konishi and Coggins [34] recently added another dimension to this important discussion, based on the two commonly observed findings from recent empirical studies: (i) that consumers are often heterogeneously and imperfectly informed about ambient environmental risks and (ii) that WTP is often highly positively correlated with averting behavior (e.g. [26] [45] [54]). Their results indicate that when consumers are imperfectly informed of exogenous environmental risks, making inferences about WTP based on individual averting behaviors can lead to significantly biased estimates and that if the marginal return to self-protection increases with the ambient environmental risk, then consumer's WTP should exhibit an inverse relationship to observed self-protection choice. Our goal in this paper is to propose a general empirical strategy to estimate WTP for exogenous environmental-risk reductions, reconciling this gap between the empirical and the theoretical findings.

Our approach consists of a contingent valuation survey design, which incorporates both revealed and stated preference data, and a standard econometric technique, known as Heckman's "dummy endogenous variable" model [31]. The survey must provide (i) a series of questions that elicit the subject's self-protective behavior, (ii) information about the relationship between self-protection activities and health risks, and (iii) a series of contingent-valuation questions. An important step is to include a reminder about a list of private risk-mitigating activities and how these activities, if properly used, reduce personal exposure. The key to the successful survey design is to pay careful attention to framing issues and to properly inform the subjects of all aspects of the contingent commodity that we intend to evaluate — i.e. the welfare value of public risk reduction *given* self-protection actions.

Econometrically, the key issue in identification and estimation is how to take care of the endogeneity of self-protection in the WTP equation. In the literature (e.g. [8] [22] [23]), a variable describing self-protection activities is sometimes included in the WTP equation, but is often found to insignificantly affect WTP. This result occurs presumably because of the covariates and the errors that simultaneously affect *both* WTP *and* self-protection. To correctly account for correlation between self-protection and WTP, we employ Heckman's dummy endogenous variable model. The Heckman's model provides an econometrically correct estimate of the welfare value of the health effects of exogenous risk reduction *conditional* on averting behavior.

We apply our empirical approach to the data set obtained by Cho, Konishi, and Easter [23] from a contingent valuation survey on arsenic contamination in drinking water. In estimation, we consider the effects of incremental addition of treatment for a variety of model specifications. The first treatment controls for the effect of providing risk information and the reminder about private risk-mitigation activities, but does not use the Heckman's model to control for the endogeneity of self-protection. The second treatment controls for both the information and the endogeneity of self-protection in estimation. Our results indicate that both the magnitude and significance of the self-protection variable increases with each treatment, and that self-protection is significantly negatively associated with WTP after the second treatment. Interestingly, even though self-protection becomes significantly negative in some specifications after the first treatment, the positive correlation between estimated WTP and self-protection could not be removed without the second treatment. These findings are consistent across all model specifications: single-bound, double-bound, and Cameronand Quiggin's bivariate [18] models.

With the double-bound model controlling for endogenous self-protection, the mean annual WTP for arsenic concentration reduction from 50 μg/L to 10 μg/L (roughly equivalent to lifetime cancer risk reduction of 25/10000 to 5/10000) is estimated to be about \$56.5 per household for the unprotected subpopulation but only \$39.9 for the protected subpopulation. We also find that the bias in WTP estimates is, as expected, larger for the tails of the distribution — those who have a high WTP for exogenous risk reduction but fail to self-protect and those who have a relatively low WTP but currently take self-protection actions. Thus our approach offers qualitatively different implications for the distribution of benefits among households. Furthermore, our results also indicate that overall mean WTP estimates tend to vary significantly across different treatments for single-bound and bivariate models, though they are largely stable for double-bound specification. This effect is closely related to the bias and efficiency of the parameter on the self-protection variable. Therefore, even if the goal of the valuation analysis is to obtain the overall relationship between (rather than the distribution of) costs and benefits, our approach may also affect its conclusions, depending on the analyst' choice of WTP elicitation methods.

Another novelty of the paper is that we apply the theoretical decomposition result obtained by Konishi and Coggins [34] in estimation of the welfare value of an hypothetical policy to inform and educate the public simultaneously with the effort to reduce arsenic risk. Somewhat surprisingly, we find that the economic value of such a joint policy is similar to that of the simple arsenic risk reduction policy. This is not, however, because the effect of the information policy is small. Rather, it occurs because of the competing effects of information and risk reduction. Overall, a smaller number of households are predicted to take self-protection actions with the information policy because the households believe the exogenous arsenic risk to be lower with the government's effort to reduce risk. This tends to yield negative welfare values. On the other hand, the welfare value of the risk reduction is higher with the information policy precisely because there are a smaller number of households who self-protect. These two effects tend to offset each other, and as a result, the overall economic value of the joint policy is similar to that of the simple risk reduction policy.

The organization of the paper is as follows. The next section reviews related literature, followed by brief discussion of a non-market valuation theory on endogenous environmental risks in Section 3. Section 4 describes our empirical strategy. We then apply our strategy in the contingent-valuation survey data and discuss the results in Section 5. The extensions of the empirical model are discussed in Section 6. The last section concludes.

2. Related Literature

There is a large literature on non-market valuation methods to estimate consumer's WTP to avoid environmental health risks. Valuation analysts may use survey-based stated-preference approach (e.g. [8] [10] [22] [35]), hedonic approach ([44] [39] [33]), averting-expenditure approach ([1] [2] [36] [40]), or an approach that combines empirical identification of dose-response relationships with the value of statistical life (VSL) estimates.[1] In all of these approaches, researchers are often concerned with endogeneity inherent in the risk valuation — consumers often take self-protective actions and thus the actual risk they face are endogenous in their actions.

In the absence of imperfect information, endogeneity of environmental health risks provides a theoretical justification for using information about individual averting behaviors to make inferences about WTP for health, safety, or environmental quality. Earlier studies (e.g. [7] [13] [24] [46]) have shown that the marginal benefit of exogenous pollution reduction equals the cost of self-protection, translated via the marginal rate of technical substitution between pollution reduction and self-protection. Until recently, however, the literature has been silent as to how one might estimate the welfare value of exogenous pollution risk reductions in the presence of imperfectly informed consumers taking endogenous self-protective activities. If consumers are perfectly informed, then analysts need not be concerned with endogeneity of averting behaviors.[2] This is because in models where consumers are perfectly informed and can optimize, compensating and equivalent variation of changes in exogenous variables such as prices and environmental quality should only depend on these exogenous variables, as consumers can perfectly optimize their endogenous choice variables. Konishi and Coggins [34], however, constructed a model in which consumers are imperfectly informed and show that making inferences about WTP based on individual averting behaviors can lead to significantly biased estimates and that if the marginal return to self-protection increases with the ambient environmental risk — the condition that holds in many practical applications — consumer's WTP will exhibit an inverse relationship to observed self-protection levels. The objective of the paper is to propose a general empirical strategy to test for the empirical applicability of this theoretical prediction.

To date, limited empirical studies have investigated the effects of exogenous risk reduction

[1] In the last approach, studies often focus on estimation of either dose-response relationships using experimental or quasi-experimental methods or the VSL, but not both. Chay and Greenstone [21] and Neidell [41] are good examples of the former while [53] is the example of the latter.

[2] Yet, the analysts might still need be concerned with possible bias in estimating WTPs based on individual averting behaviors as shown in Shogren and Crocker [47] [48].

when consumers engage in endogenous averting behaviors. Neidell [41] recently estimated the effect of ozone pollution on asthma hospitalization controlling for endogenous averting behavior. He finds that accounting for averting behavior drastically increases the estimated effect of ozone for children and the elderly, implying that conventional dose-response estimates were biased downward. Our results are consistent with this finding — our estimated economic value of exogenous risk reduction is significantly higher for households without self-protection than those with self-protection. However, our approach differs from Neidell on two important accounts. First, we combine contingent valuation data with (reported) averting behavior and use Heckman's approach to control for endogeneity while Neidell [41] uses reduced-form regression with air quality information, rather than avoidance behavior, as an independent variable. With insufficient data on avoidance behavior, Neidell was unable to recover the structural parameter on averting behavior. Second, our approach allows us to directly estimate consumer's willingness-to-pay for reduction of environmental risk, instead of the health effect of risk reduction.

In earlier studies, endogenous regressors are often omitted from the WTP estimation, following the recommendation offered in McConnell [37]. This recommendation is partly because of the anticipated bias in estimated parameters and partly because its inclusion in valuation functions is contrary to the spirit of valuing *exogenous* changes (in models with perfectly informed consumers). More recently, however, an increasing number of studies have included potentially endogenous variables in estimation of the WTP function, possibly because of increasing interest in sources of variation in WTP estimates (e.g. [8] [22] [50] [58]). The problem, of course, is that the estimated parameters will be inconsistent if these variables are indeed endogenous and the endogeneity is not appropriately controlled.[3] When open-ended or payment card formats are used in valuation studies, one can use standard instrumental variable approaches to properly correct for endogeneity. If, on the other hand, dichotomous-choice or discrete-choice formats are used — the case we consider — one can use Heckman's dummy endogenous variable model and estimate it with full-information maximum likelihood procedures.

Our empirical approach is most closely related to Cameron and Englin [17] and Whitehead [57]. Both papers jointly estimate WTP and an endogenous variable, which also enters the WTP equation as one of the regressors. Cameron and Englin [17] model the relationship between respondent experience in fishing and WTP to improve trout habitats. They find that WTP jumps as respondent experience increases from zero and more experience decreases conditional variance of WTP. In estimating the benefits of water quality improvements, Whitehead [57] combined stated-preference and revealed-preference data and jointly estimated WTP and recreational trip decisions to control for endogeneity of the number of recreational trips included in the WTP equation. The author finds that the estimated magnitude of the effect of the endogenous variable increases after controlling for endogeneity, resulting in the statistically significant difference in the estimated use values. In these papers, the interest lies in consistency and efficiency of the conditional WTP as is

[3]Note, however, that unconditional WTP statistics (e.g. $E(WTP)$) are still unbiased (see [20]) and conditional WTP statistics (e.g. $E(WTP|X)$) are inconsistent regardless of inclusion or exclusion of endogenous variables if not controlled for endogeneity.

the case with our paper.

Our paper extends this line of research in three important regards. First, we consider valuation of environmental health risk reduction rather than environmental quality improvements. In environmental quality improvements, endogenous choice variables (such as recreational visits) and WTP to improve environmental quality (such as habitat quality or quality of freshwater resources) are expected to have a positive relationship both in theory and in empirical applications. For example, in the Cameron-Englin study, WTP to improve trout habitats are expected to increase with fishery experience. In ours, however, we are attempting to reconcile the gap between the positive relationship found in empirical studies, on one hand, and the negative relationship predicted in theory, on the other, between self-protection and WTP. Second, we consider the effects of information treatment in the survey as well as endogeneity control in estimation. We show that a reminder about the effect of self-protection (along with relevant risk information) per se can influence respondents' WTP values significantly, but the positive relationship between WTP values and self-protection levels could be removed only after including both information treatment and endogeneity control. Lastly, we also exploit the averting behavior model to estimate the economic value of a policy to mitigate exogenous risks and to simultaneously inform the public about the risk mitigation.

3. A Non-market Valuation Theory Revisited

Environmental risks are *endogenous* in consumers' private averting actions. Because consumers can and often do take costly actions to avoid unpleasant consequences of ambient or *exogenous* environmental risks, the welfare values of reducing the exogenous environmental risks depend upon consumer behavior. Konishi and Coggins [34] point out that simply using revealed preference data or providing all information in a contingent valuation study including the level of ambient environmental risks does not resolve this endogeneity and is still likely to result in misdirected policy decisions.

Consider an ambient risk $r \in [0, r_{\max}]$ that poses environmental risks to humans. Assume that defensive measures ("self-protection") s can be taken to mitigate risk. Assume there is a health production function $h(s, r)$ relating the levels of self-protection and ambient risk with health outcomes. Let F be a consumer's belief about the ambient risk. Finally, assume that there is an objective measure of the true ambient risk $\hat{r}$. Though it may be difficult to specify a truly objective measure in practice, this assumption is consistent with the existing literature (e.g. [14] [46] [47]) and this evaluation point $\hat{r}$ must be based on the best expert judgement as argued in Viscusi and Gayer [52].[4] Each individual chooses a privately optimal level of self-protection s^* given F.

A central question we need to ask is, what is the welfare value of changing $\hat{r}$ from $\hat{r}_0$ or $\hat{r}_1$ given her choice s^* when the government may not be able to effectively affect her belief F about $\hat{r}$ (both before and after the policy change)? Let us first consider the case in which the consumer belief F

[4] Note that health risks are inherently random, though I do not explicitly address randomness for simplicity of arguments and notation. For those who wish to have probabilistic interpretations, consider $\hat{r}$ to be the underlying state of the risk, based on the expert judgement, that generates a certain distribution of health outcomes given s.

is outside the government control. This question is important, because we need to evaluate the benefit, either aggregate or per capita, of reducing ambient environmental risk for a population consisting of heterogeneous consumers, with each person i having chosen a varying level of s_i^* according to his or her risk perception F_i. To this end, the valuation analyst should not allow her to consider adjusting her behavior optimally, in the survey response, according to the true information $\hat{r}_0$ or $\hat{r}_1$. Hence, her self-protection is fixed at the pre-evaluation level $s^*(F)$.

Two strategies are feasible. One way is to use dose-response information to evaluate changes in health outcomes (i.e. from $h(s^*, \hat{r}_0)$ to $h(s^*, \hat{r}_1)$) for varying levels of s^* and use the estimated value of changes in h. This approach is similar to that used in Neidell [41]. Given the distribution of s^* over the population, we can estimate the aggregate benefit. Another approach is to conduct a contingent-valuation study where the analyst must ask her to evaluate her exposure to health risks associated with $s^*(F_0)$. After letting her recognize $h(s^*(F_0), \hat{r}_0)$ and $h(s^*(F_0), \hat{r}_1)$, he asks her "Given your choice $s^*(F_0)$, how much would you be willing to pay for a change from $\hat{r}_0$ to $\hat{r}_1$ (or alternatively, from $h(s^*(F_0), \hat{r}_0)$ to $h(s^*(F_0), \hat{r}_1)$)?" Note that because the analyst needs to evaluate her WTP at the correct $\hat{r}$, whichever policy variable, $\hat{r}$, p, or F changes, the true information $\hat{r}$ needs to be presented to the individual if a contingent valuation framework is used. The key here is to recognize the difference between the information or belief F on which the individual's prior self-protection decision is based and the information $\hat{r}$ on which the individual's welfare evaluation is based. In the next section, we propose a general survey and econometric procedure, which is relatively easy to employ, but can correctly estimate the contingent value in question.

Though our subsequent analysis primarily focuses on the case where consumer's belief F (and therefore her self-protection level s^*) is fixed before and after the government's policy to change $\hat{r}$, our approach is also amenable to the case in which the government simultaneously launches large-scale educational programs to inform and educate consumers about the change from $\hat{r}_0$ or $\hat{r}_1$. In this case, the analyst must evaluate the welfare value of the changes in health outcomes from $h(s^*(F_0), \hat{r}_0)$ to $h(s^*(F_1), \hat{r}_1)$ where F_1 is the consumer's belief upon receiving information about new risk level $\hat{r}_1$. Our interest lies in estimating the *ex ante* value of such a joint policy. Konish and Coggins [34] show that the welfare value of this joint policy can be decomposed into two components — the welfare value of the information program (i.e. changes in s^* given $\hat{r}$) and that of the cleanup policy (i.e. changes in $\hat{r}$ given s^*). Our approach can be combined with this decomposition result to yield a sensible welfare estimate of this policy.

4. The Empirical Strategy

Our empirical strategy consists of a contingent valuation survey design, which incorporates both revealed and stated preference data, and a standard econometric technique, known as Heckman's dummy endogenous variable model.

A. The Survey Design

We need to design a contingent valuation survey in a way that allows the respondent to evaluate her personal exposure to health risks given her self-protection level. Therefore, the survey consists of (i) a series of questions that elicit the subject's self-protective behavior, (ii) information about the relationship between self-protection activities and health risks, and (iii) a series of contingent-valuation questions.

In step (i), for example, the analyst would ask what kind of water treatment she uses and whether or not she uses bottled water for drinking purposes in the case of drinking water quality or whether or not she uses an artificial mask or reduces outdoor activities according to health advisories in the case of air quality. It is important that the analyst properly elicits what the subject would *normally* do given her current belief.

In step (ii), the survey provides all necessary information about the environmental risk of interest, from general health risk information to information on personal exposure levels. It is advisable to insert a reminder about a list of private risk-mitigating activities and how these activities, if properly used, reduce personal exposure.

After steps (i) and (ii), the analyst would introduce a series of willingness-to-pay questions. Though we focus on a single-bounded dichotomous-choice format in the subsequent sections for ease of exposition, other formats can be readily incorporated.

B. The Dummy Endogenous Variable Model

Provided that we have collected all relevant information from the sample of survey respondents, the key econometric issue is to correct for the endogeneity of self-protection in willingness-to-pay estimation. As we shall demonstrate in Section 4, this endogeneity can cause a serious bias in the WTP estimates. Conventionally, it is argued that covariates in the WTP equation do not influence the estimates of the *unconditional* WTP distribution or statistics (i.e. $E(y^*)$ or $med(y^*)$) (e.g. [20]). This is because including respondent i's covariates in the WTP equation adds no information about the distribution of y_i^* *after* incorporating i's yes-no response to a particular bid value. That is, the probability of y_i^* being greater than or equal to the bid value given the observed yes-no response to that bid is the same regardless of information on covariates. However, policy makers are often interested in the distribution or statistics of WTP *conditional* on a set of covariates (i.e. $E(y_i^*|x_i)$ or $Med(y_i^*|x_i)$). The conditional statistics will be generally biased if there are omitted variables or variables correlated with error terms, for in such a case the parameters of the covariates will be biased ([28], p.679). In our case, we are interested in the distribution of WTP conditional on self-protection. As WTP is likely to be correlated with self-protection, the conditional distribution of WTP may be biased. We need to remove risk perceptions and attitudes embodied in self-protection in order to correctly estimate the conditional mean or median of WTP.

To correctly account for the correlation between self-protection and WTP, we employ Heckman's dummy endogenous variable model. The WTP estimation can be framed as a joint decision of two endogenous variables, a WTP response and a self-protection action. In what follows, we explicitly consider the case in which we observe a single-bound dichotomous WTP response and a binary response on self-protection action. However, extensions to double-bound WTP responses, correlated WTP responses (i.e. due to starting-point and anchoring biases), and ordinal or multinomial self-protection actions are relatively straightforward, and we estimate these alternative specifications and present the results in Sections 5 and 6.

Let y_i^* be individual i's willingness-to-pay, s_i^* self-protection level, and X_{1i}, X_{2i} exogenous variables. There are two dummy variables, y_i (WTP response) and s_i (self-protection response), defined by

$$
\begin{aligned}
y_i &= 1 \text{ iff } y_i^* > t_i, \\
y_i &= 0 \text{ otherwise,}
\end{aligned}
$$

and

$$
\begin{aligned}
s_i &= 1 \text{ iff } s_i^* > 0, \\
s_i &= 0 \text{ otherwise,}
\end{aligned}
$$

where t_i is the bid value assigned to i.

Following Heckman [31], we write the estimation model as follows:

$$
y_i^* = X_{1i}\alpha_1 + s_i\beta_1 + s_i^*\gamma_1 + \epsilon_{1i}, \tag{1a}
$$

$$
s_i^* = X_{2i}\alpha_2 + y_i\beta_2 + y_i^*\gamma_2 + \epsilon_{2i}. \tag{1b}
$$

and

$$
\begin{aligned}
&E(\epsilon_{ji}) = 0,\ \ E(\epsilon_{ji}^2) = \sigma_j,\ \ E(\epsilon_{1i}\epsilon_{2i}) = \sigma_{12},\ \ j = 1, 2, i = 1, ..., n. \\
&E(\epsilon_{1i}\epsilon_{2i'}) = 0 \ \text{ for } i \neq i'.
\end{aligned}
$$

Using economic intuition, we can restrict some of the parameters of the model: $\beta_2 = \gamma_2 = 0$. By assumption, the survey response y_i should not be available to person i when she makes her self-protection decisions, so y_i cannot influence s_i^* retrospectively. Thus, the "structural shift" parameter $\beta_2 = 0$. Similarly, i's willingness-to-pay to reduce ambient risk level $\hat{r}$, conceived at the time of the survey, should not influence s_i^* retrospectively. Thus, the spurious effect $\gamma_2 = 0$. Note that correlations between y_i^* and s_i^* that may arise due to consumer's risk attitudes and risk perceptions are already accounted for by including relevant covariates in X_1 and X_2 and by allowing for correlation between ϵ_{1i} and ϵ_{2i}. With $\beta_2 = \gamma_2 = 0$, the model satisfies the "principal assumption", $\gamma_2\beta_1 + \beta_2 = 0$ ([31], p.936), and therefore, is well-defined. If y_i^* or s_i^* or both are observed or continuous variables, the model becomes an instrumental variable model or a system of simultaneous equations.

Lastly, γ_1 may be either zero or non-zero. It measures the extent to which the level of self-protection consumer i is *normally* willing to take influences her willingness-to-pay to reduce ambient risk level $\hat{r}$. In what follows, we will simply work with the case $\gamma_1 = 0$, because the model with $\gamma_1 \neq 0$ can be analyzed essentially the same way as with $\gamma_1 = 0$, with some notational modifications.[5] Now the model is:

$$\begin{aligned} y_i^* &= X_{1i}\alpha_1 + s_i\beta_1 + \epsilon_{1i}, && (1a') \\ s_i^* &= X_{2i}\alpha_2 + \epsilon_{2i}. && (1b') \end{aligned}$$

Our main interest lies in estimating $E(y^*)$ or $Med(y^*)$ as well as $E(y^*|X,s)$ or $Med(y^*|X,s)$.

As long as we are willing to assume the joint distribution of ϵ_{1i} and ϵ_{2i}, we will be able to obtain consistent and efficient estimates of the parameters of the model using full-information maximum likelihood method. Note that as Greene [27] demonstrates, we can ignore the recursive nature of the right-hand variables s_i in the first equation of **(1)** in formulating the log-likelihood,[6] and the full-information maximum likelihood estimation is the preferred estimation approach. Just like in the conventional WTP estimation, we will also be able to identify and estimate σ_1 by including t_i as one of the regressors. As with the standard model, we assume y_i^* to follow a log-normal distribution, and therefore, with $\ln y_i^*$ in place of y_i^*, $(\epsilon_{1i}, \epsilon_{2i})$ follows a bivariate normal distribution.

The log-likelihood function for model $(1')$ with a bivariate normal distribution takes the following form:

$$\begin{aligned} \mathcal{L} = \sum_i \Big\{ & y_i s_i \log\left[\int_{\nu_{1i}}^{\infty}\int_{\nu_{2i}}^{\infty} \phi_2(z_{1i}, z_{2i}, \rho) dz_{2i} dz_{1i}\right] \\ & + y_i(1-s_i)\log\left[\int_{\nu_{1i}}^{\infty}\int_{-\infty}^{\nu_{2i}} \phi_2(z_{1i}, z_{2i}, \rho) dz_{2i} dz_{1i}\right] \\ & + (1-y_i)s_i\log\left[\int_{-\infty}^{\nu_{1i}}\int_{\nu_{2i}}^{\infty} \phi_2(z_{1i}, z_{2i}, \rho) dz_{2i} dz_{1i}\right] \\ & + (1-y_i)(1-s_i)\log\left[\int_{-\infty}^{\nu_{1i}}\int_{-\infty}^{\nu_{2i}} \phi_2(z_{1i}, z_{2i}, \rho) dz_{2i} dz_{1i}\right]\Big\} \qquad (2) \end{aligned}$$

where $\phi_2(\cdot, \rho)$ is a standard bivariate normal density with a correlation coefficient ρ, $\nu_{1i} = (\ln t_i -$

[5] To see this, substitute s_i^* into the first equation with the restriction $\beta_2 = \gamma_2 = 0$ and rewrite it to obtain:

$$\begin{aligned} y_i^* &= X_1\alpha_1 + X_2\theta_2 + s_i\beta_1 + u_{1i}, \\ s_i^* &= X_2\alpha_2 + u_{2i}, \end{aligned}$$

where

$$\begin{aligned} \theta_2 &= \alpha_2\gamma_1, \\ u_{1i} &= \epsilon_{1i} + \epsilon_{2i}\gamma_1, \\ u_{2i} &= \epsilon_{2i}. \end{aligned}$$

[6] The argument is trivial. For example, $\Pr(y_i = 1, s_i = 1) = \Pr(y_i = 1|s_i = 1)\Pr(s_i = 1)$ by the definitions of joint and conditional probabilities. In this equation, the event $y_i = 1$ is observed conditional on $s_i = 1$. Suppose that ϵ_{1i} and ϵ_{2i} follow a bivariate normal. Then, $\Pr(y_i = 1|s_i = 1) = \Phi_2(X_{1i}\alpha_1 + s_i\beta_1, X_{2i}\alpha_2)/\Pr(s_i = 1)$. Substituting this into the above identity, we see that $\Pr(y_i = 1, s_i = 1) = \Phi_2(X_{1i}\alpha_1 + s_i\beta_1, X_{2i}\alpha_2)$. Thus, the likelihood function is the same as if we ignore the recursive nature of the self-protection variable.

$X_{1i}\alpha_1 - s_1\beta_1)/\sigma_1$, and $\nu_{2i} = -X_{2i}\alpha_2/\sigma_2$. With $\ln t_i$ as one of the regressors, we can use standard bivariate probit algorithms such as in STATA or LIMDEP to maximize the log-likelihood function **(2)**. The resulting point estimates can then be transformed to yield the regression-like WTP equation [16] and the associated variance-covariance estimates can be transformed using the formula offered in Patterson and Duffield [43]. Extension of the model to the case of double-bound data is straightforward.[7]

5. Illustrations with An Empirical Example

A. Brief Description of the Data

The significance of endogenous self-protection in eliciting the contingent values of exogenous environmental risk reduction is illustrated with a contingent-valuation study that attempts to estimate the willingness-to-pay to reduce arsenic concentration levels in drinking water from $50\mu g/\text{L}$ to $10\mu g/\text{L}$ in Minnesota communities. The survey area consists of 30 communities in Minnesota that have had an arsenic contamination problem at least once during the 2000-2006 period. After a pretest survey, a formal mail survey was conducted in March through April 2007. Of our 990 randomly sampled households, 530 returned their responses. Out of 530, 109 respondents did not obtain their water from the city water systems (20.5%) and 28 respondents (5.3%) refused to answer because they were living in a nursing home, dislike surveys, or did not know enough about the water-quality issue to answer the questions. After curtailing observations that failed to provide information about income, education, children in the household or averting behavior, the usable sample size was 307.

The survey consists of a series of questions that elicit (i) respondents' perceptions about arsenic risks, (ii) self-protection levels, and (iii) dichotomous-choice WTP responses before and after providing complete arsenic information. The arsenic information sheet included actual contamination levels in their drinking water that varied across different communities. It also included a reminder about effective self-protective activities against arsenic risks:

> Water softeners and activated carbon filters do not reduce arsenic levels effectively. The following treatment devices, if used properly, will reduce arsenic level below $10\mu g/\text{L}$: (A) installation of reverse osmosis (RO) treatment; (B) installation of distillation treatment; (C) installation of activated alumina treatment, and (D) bottled water for preparation of foods and drinking. All treatment devices require regular maintenance.

The contingent-valuation question was designed to ensure that each respondent understands she is being asked to evaluate her WTP to reduce *ambient* levels of arsenic concentrations in her drinking water rather than her personal exposure:

[7] An appendix describing the extension to double-bound data is available from the authors upon request.

> Would you be willing to pay $___ annually ($___ per month), in excess of your current water bills, for strengthening the water quality standard by lowering the permitted level of arsenic from $50\mu g/\mathrm{L}$ to $10\mu g/\mathrm{L}$?

The data set allows us not only to examine the extent to which conventional WTP estimates are biased and whether or not the empirical strategy proposed in the previous section appropriately elicit the correct WTP values but also to empirically investigate the interrelationship between consumers' information acquisition, self-protection decisions, and expressed welfare values.

B. Risk Perception and Self-protection

It is well documented that (i) consumers' WTP for public environmental-risk reduction are positively correlated with averting or precautionary behaviors (e.g. [42] [45]), (ii) consumers' perceptions of environmental risk are highly heterogeneous (e.g. [25] [54]), and (iii) consumers' risk perceptions are often biased or based on inaccurate information (e.g. [49] [52] [54]). The results presented in this subsection reiterate these points.

Table 1 reports the distribution of the survey respondents' perceptions about arsenic risks from drinking water, before and after reading the Arsenic Information Sheet. R_0 (R_1) is an index from 1 to 10 that measures respondent's perception of arsenic risks in drinking water before (after) giving information, with 1 being "very unsafe" and 10 being "very safe." The survey question was designed to elicit consumer perceptions about *exogenous* arsenic risk levels *before* use of home treatment.

[Table 1]

The table confirms that consumer perceptions are highly heterogeneous. Moreover, about 56% of the survey respondents changed their perception after reading the Information Sheet. The mean of the difference between R_0 and R_1 is 0.26 (1.19 in absolute value), suggesting that on average, respondents slightly overestimated, rather than underestimated, arsenic risks. This finding is consistent with the existing risk perception literature that consumers tend to overestimate low probability events (see [52] and papers cited therein). In general, however, the changes in risk perceptions were also highly heterogeneous. This evidence may suggest that respondents' prior perceptions were biased and based on somewhat inaccurate information. This point is further reinforced by the fact that about 82% of the respondents found the information sheet useful in improving understanding arsenic issues.

The survey identified three types of averting behavior: (a) filter or removable treatment, (b) bottled water, (c) installed treatment system (i.e. RO, distillation, or activated alumina treatment). We define the ordered categorical variable, Action, which ranges from 1 to 5 and measures the level of precautionary behavior as follows: Action = 1 if a respondent takes no precautionary action, = 2 if uses filter or removable treatment only, = 3 if uses bottled water only, = 4 if uses both filter and bottled water but not installed treatment, and = 5 if uses installed treatment.

Figure 1 reports the mean WTP estimates from conventional double-bound WTP estimation before and after information provision, for different subsamples taking varying levels of precautionary action.[8] The figure clearly indicates a descending trend in the number of respondents and an ascending tread in the mean WTP. This result is consistent with the idea that the consumer who is willing to pay more for exogenous risk reduction also tends to take precautionary actions to self-protect. This is precisely the source of bias that the valuation analyst needs to be concerned with *if the objective is to estimate the welfare value of the health effects of exogenous risk reduction, conditional on averting behavior*. In our case, because two of the precautionary actions, bottled water and installed treatment, can reduce personal exposure to arsenic risks in drinking water, the health effects of exogenous risk reduction on the unprotected population (i.e. Action = 1-3) must be larger (therefore, the WTP estimates higher) than on the protected population (Action = 4 or 5).

[Figure 1]

C. The Empirical Results

In estimating the model (1), we assume that y_i^* in (1a$'$) follows a log-normal distribution. The exogenous variables in X used for estimation are defined in Table 2, along with their descriptive statics. To demonstrate the importance of endogenous self-protection in WTP estimates, we present our results in order of incremental addition of treatment. We first estimate the WTP equation (1a$'$) using the WTP responses prior to giving information about arsenic risks and effective self-protective activities ("risk information" treatment). We then estimate the WTP equation using the WTP responses after giving the risk information, but without controlling for endogeneity of self-protection variable ("endogenous self-protection" control). Lastly, we estimate the full model (1), using the WTP responses after giving risk information and accounting for endogenous self-protection. Since it is well known that double-bound models are more statistically efficient than single-bound models (e.g. [30]), we estimate these three models using both single-bound and double-bound data. There are two types of averting behavior in our context, "arsenic-related" and "non-arsenic-related" behavior. Because s_i must represent self-protection that can change i's personal exposure to arsenic risks, we used a binary dummy variable, Protect, which equals 1 if a respondent uses bottled water as a main source of drinking water or an installed system designed to treat arsenic and 0 otherwise.

[Table 2]

[8]The naive WTP estimates were obtained by the standard double-bound estimation, assuming the log-normal distribution and using Action, Age, Sex, Child, Edu, and Log(Y) as regressors.

The estimation results are presented in Table 3. All coefficients and standard errors in the WTP equation are transformed with the delta method described in Patterson and Duffield [43]. Signs and significance levels of the estimated parameters are surprisingly similar and stable across all models, and they are mostly in line with our expectations. However, one notable difference is that Protect in the WTP equation becomes more significant and larger in magnitude with each additional control (i.e. risk information and endogenous self-protection), for both single-bound and double-bound estimates. The sign of Protect is negative and significant at 10% level when controlling for endogeneity of self-protection and correlation of errors ϵ_1 and ϵ_2, which suggests that the welfare value of exogenous risk reduction is higher for the unprotected subpopulation. Furthermore, the log-likelihood also improves with each additional control.

[Table 3]

R_1 (R_0) and log(income) are significant determinants of WTP to reduce arsenic risks in drinking water. Somewhat surprisingly, other demographic variables Age, Sex, Child, and Edu were insignificant. We suspect that this result occurs for two reasons. First, the survey asks a respondent's willingness to pay for arsenic risk reductions as an increase in the water bill. It is likely that the respondent inferred that the arsenic risk reduction in tap water and the increased water bill would affect his or her household as a whole rather than themselves as an individual. Thus, their *individual* demographic characteristics did not significantly affect the WTP. Second, these demographic variables were highly correlated with R_0 and R_1. Thus, provided that R_1 (R_0) is a significant determinant of WTP, the demographic variables did not influence WTP after controlling for the risk perception.[9]

Analogous comments apply to the self-protection equation. Prior perceptions about arsenic risks and taste are significantly associated with self-protection: the respondent is more likely to use some self-protection measure if she perceives a higher level of arsenic risks or feels that tap water tastes bad. The coefficient on log(income) was also significantly positive. Other demographic variables Age, Sex, Child, and Edu were insignificant, possibly for the reasons similar to the WTP equation.

Following [16], the mean and median WTP estimates are computed and also presented in Table 3. The relatively small WTP estimates are obtained primarily because the survey asks willingness-to-pay for the arsenic risk reduction that is essentially a "gray" zone. Reductions in cancer morbidity and skin effects that can result from strengthening the water quality standard from $50\mu g/\mathrm{L}$ to $10\mu g/\mathrm{L}$ are not large. As expected, the mean WTP estimates from single-bound models are less efficient than those of double-bound models. Interestingly, however, the standard deviation of estimated $E(WTP_i)$ increases with each addition of treatment. As we shall see below, this result occurs precisely because of the endogenous self-protection.

[9] The signs and significance levels of the model parameters are stable across specifications with different sets of regressors. Selected results on double-bound estimation with endogenous self-protection are reported in Appendix.

Figure 2 compares the mean and the 25th, 50th, and 75th percentiles of estimated WTP for these models.[10] Even though Protect variable has a significantly negative coefficient after risk information treatment (models 2 and 4), the estimated WTPs still tends to increase with this self-protection variable. In contrast, the estimated WTPs after controlling for endogenous self-protection are clearly decreasing in self-protection. Intuitively, this negative relationship is obtained because there are consumers who are currently not self-protecting due to imperfect information while they would be willing to pay a large amount for risk reduction if given more accurate risk information, and vice versa. We should expect this effect to be stronger for the tails of the distribution — those who are currently self-protecting but have relatively low WTP for risk reduction should express significantly low WTP while those who are not currently self-protecting but have relatively high WTP should express significantly high WTP. The estimated 25th and 75th percentiles of WTPs seem to confirm this effect. Furthermore, WTPs estimated from single-bound models, as expected, exhibit larger variances than those from double-bound models. Interestingly, the single-bound model with endogenous self-protection predicts very high WTP values for the upper tail of the distribution of the unprotected subsample, bringing its mean significantly higher than that of the protected. We suspect this spurious effect occurs due to statistical inefficiency of single-bound estimation. The marginal effect of the Protect variable on expected WTP at the mean of the data is $-\$120.40$ for the single-bound model. This spurious effect seems to be handled well with double-bound estimation, with a much smaller marginal effect of $-\$35.07$.

[Figure 2]

U.S. EPA estimated the average annual compliance costs per household of the new arsenic rule to be approximately $39.76 (adjusted for 2008 U.S. dollars). Given this uniform cost estimate, Table 4 reports the estimated proportions in each subpopulation of those who gain from the new arsenic rule ("winners").[11] The table assumes that community water systems would increase water bills in order to cover the compliance costs as they often do in practice. In all models except models 1 and 4, a median-voter household would reject this new rule. If, on the other hand, we use the mean WTP estimates, the new arsenic rule would be accepted with all models. Thus, if the objective of the analysis is to make policy evaluations based on comparison of aggregate or average costs and benefits, our approach may not offer immediate advantages over conventional approach. However, if the objective is to obtain more accurate estimates of welfare values of health effects from reduced arsenic risks conditional on self-protective activities or to identify important distributional consequences, as recommended by Arrow and other economists [6], then our approach does offer significant advantages. First, we see important differences in the distribution of winners. The

[10] Following Cameron [16], we computed expected values of individual WTPs by $E(WTP_i) = \exp(X_i\hat{\beta} + .5\hat{\sigma}^2)$ and calculated the mean and the percentiles of these values for the two subsamples for each model.

[11] Actual cost burden for each household varies by community size, community's treatment technology, and household size. The cost-benefit analysis presented here is for illustrative purposes only.

models without endogenous self-protection predict that 41% (single-bound) and 40.5% (double-bound) of the unprotected households gain from the new rule while 53.3% (single-bound) and 50.5% (double-bound) of the protected households gain from the new rule. In contrast, the models with endogenous self-protection predict that 50.5% (single-bound) and 49% (double-bound) of the unprotected households gain from the new rule whereas only 23.4% (single-bound) and 20% (double-bound) of the protected households would support the new arsenic rule. Second, even if a median voter rejects the new arsenic rule, we may still justify the new rule from a public health point of view, arguing that unprotected households account for roughly 2/3 of the community population and there are still significant gains for unprotected households. Moreover, the mean WTP estimate of $50.7 (double-bound), combined with this distributional information, implies a possibility that the compliance cost of $39.76 could be successfully financed via community-wide Lindahl taxes, asking for more contributions from those who currently do not self-protect but are estimated to have a large WTP once aware of arsenic risks.

[Table 4]

D. Value of Information

In the preceding analyses, we have assumed that the population outside the contingent valuation study would not be informed of the new exogenous risk level $\hat{r}_1$ and therefore would not change their self-protective actions. The implicit assumption we are making here is that effective information programs are costly, and the government is lax in informing and educating the public about important risk regulations. We demonstrate below, however, that our approach can be used to analyze the case where the government simultaneously launches an effective education program and consumers adjust their self-protection levels accordingly.

To estimate the welfare value of such a joint policy, we utilize the decomposition result (Proposition 3) of Konish and Coggins [34], and sequentially estimate the welfare values of health effects of the information program (i.e. from $h(s^*(F_0), \hat{r}_1)$ to $h(s^*(F_1), \hat{r}_1)$) and of the new arsenic rule (i.e. from $h(s^*(F_1), \hat{r}_0)$ to $h(s^*(F_1), \hat{r}_1)$).[12] The sum of these two estimates should approximate the welfare value of the joint policy. The key to estimating these welfare values is to obtain the prediction of consumer perception F_1 upon receiving risk information $\hat{r}_1$ and the prediction of self-protection level $s^*(F_1)$. Since we have information on risk beliefs, R_0 and R_1, before and after informing the respondents about true arsenic concentration levels, we estimate a two-limit Tobit model regressing R_1 on R_0, ArsenicCurr, and ArsenicHist, following Smith and Johnson [49].[13]

[12]This implicitly assumes the following timing of events. The government announces its new policy to change $\hat{r}_0$ to $\hat{r}_1$, launches the information program, which affects consumer's belief from F_0 to F_0 and thereby changes her self-protective action from $s^*(F_0)$ to $s^*(F_1)$, and finally enforces its policy and achieves $\hat{r}_1$.

[13]The estimated equation is as follows (standard erros in parenthesis).

$$R_1 = \underset{(.445)}{2.445} + \underset{(.013)}{.860}\, R_0 - \underset{(.020)}{0.071} ArsenicCurr - \underset{(.051)}{.029}\, ArsenicHist.$$

We replace the values of ArsenicCurr with the new arsenic rule of 10 $\mu g/L$ if ArsenicCurr exceeds the standard. The predicted values of R_1 are then used as approximations to F_1. To obtain predicted self-protection levels, we use the self-protection equation from regression model 6, with the predicted values of R_1 in place of R_0. The welfare values are then estimated respectively as:

$$
\begin{aligned}
V_i^{\text{Info}} &= E[WTP_i|s_i = s_i(R_0)] - E[WTP_i|\hat{R}_1(\hat{r}_1), s_i = s_i(\hat{R}_1(\hat{r}_1))],\\
V_i^{\text{Rule}} &= E[WTP_i|s_i = s_i(\hat{R}_1(\hat{r}_1))],\\
V_i^{\text{Total}} &= V_i^{\text{Info}} + V_i^{\text{Rule}}.
\end{aligned}
$$

Note that our empirical estimate is only an approximation to the Konishi-Coggins welfare measure for two reasons. First, the decomposed welfare values in Konishi and Coggins are evaluated at *perfect* information — the subject must "know" both $\hat{r}_0$ and $\hat{r}_1$ in evaluating her WTP — while in our empirical context, we expect the survey respondents to have formed somewhat subjective perceptions about arsenic risks upon receiving risk information. Second, to follow the Konishi-Coggins decomposition exactly, one needs to evaluate the difference between the welfare costs of imperfect information at $(s^*(F_0), \hat{r}_0)$ and $(s^*(F_1), \hat{r}_1)$. But we approximate this difference by the difference in WTP for arsenic risk reduction at $(s^*(F_0), \hat{r}_1)$ and $(s^*(F_1), \hat{r}_1)$.

The estimated means of these welfare values are presented in Table 5. As expected, the estimated mean welfare value of the joint policy is slightly higher than that of the new regulation without the information program, but the difference between the estimates is very small. This result, however, does not imply that the information program has statistically insignificant effects on average[14] or that the information program has small welfare effects. Rather, this occurs because the information program and the new arsenic regulation have competing welfare effects. Indeed, as shown in columns 4 and 5, our model predicts that households respond to the information program very actively. However, while we predict that some households would take self-protective actions that they are currently not taking, others decide to forgo self-protective actions that they are currently taking precisely because they believe the risks to be lower with the new rule. Overall, a smaller number of households are predicted to take self-protective actions with the information program. The estimated welfare value of information is thus negative on average. At the same time, the welfare value of the new arsenic rule is larger with than without the information program, because there are more households who do not self-protect. These effects offset each other, and at least in this particular example, result in the overall welfare value similar to that without the information program. There are, however, important distributional differences between the two policies. Figure 3 reports the distribution of welfare values for each policy for two subpopulations. While the new arsenic rule has positive welfare values for *all* households without the information program, the joint policy can result in negative welfare values for some households. Intuitively, this occurs because of the disparity between private and public valuation of risk reduc-

[14] Paired sample t-test rejects the null that the mean of the difference between the two welfare values is zero at 5% significance level.

tion — some households decide not to self-protect when the public valuation (which we estimated from the valuation study) predicts they should.

[Table 5]

[Figure 3]

One caveat is that the method used here to obtain the welfare value of information is highly sensitive to prediction of self-protection activities. The model predicts that about 27% of the households in sample change their self-protection levels and 57% of those who currently self-protect would choose not to self-protect in response to the new arsenic rule. We expect this prediction to be somewhat spurious. Many of the households use bottled water or installed treatment not only for protection against arsenic risks, but also for protection against other contaminants such as copper or simply for better taste of water. Increased precision in the prediction of self-protection would increase our confidence in the estimated value of information.

6. Discussion — Extensions of the Model

The empirical model (1) presented in Section 4 is sufficiently general, and can be extended to incorporate various issues that may arise in real valuation settings. In this section, we discuss two issues, correlated WTP responses and ordered or multinomial averting behavior data.

A. Correlated WTP Responses

In the contingent valuation study with follow-up questions, the assumption that respondents refer to the same underlying WTP value in answering the first and follow-up questions is considered questionable in many applications. Statistically, the endogeneity of the two WTP responses occurs, because the probability of receiving, *and* saying yes/no to, the follow-up bid value is often not independent of the first response. The most well known source of endogeneity is starting-point bias. Starting-point bias may occur, for example, if respondents interpret the first bid amount as being the "socially correct" amount and have the motive to say yes or no to the socially correct answer, if respondents anchor their underlying WTP to the initial bid ("anchoring effect"), or if respondents have a high propensity to say "yes"/"no" to *any* bid ("yea-saying/nay-saying effect"). The presence and likely causes of starting-point bias are well documented (e.g. [5] [9] [11] [12] [38]).

To address the anchoring effect, Herriges and Shogren [32] proposed a Baysian framework in which respondents' WTP values are weighted averages of the prior and the bid values while Cameron and Quiggin [18] suggested a bivariate probit model in which the initial WTP and the second WTP values are allowed to vary and correlate. Both of these models have been used in subsequent studies (e.g. [3] [22] [55]).

To take care of the yea-saying/nay-saying effect, Whitehead [55] [56] proposed a random-effect probit model by treating the iterative valuation data as pseudo-panel data. Assuming only the yea-saying effect, Chien *et al.* [22] considered a model with the composite error, which consists of a standard normal error and a non-negative half-normal error. In each case, there exists a corresponding likelihood function that can also incorporate endogenous self-protection decision, and we can use full-information maximum likelihood procedures to estimate it. Unfortunately, both models impose somewhat restrictive assumptions on the disturbance structures besides the standard asymptotic normality assumption. Because the misspecification of the error structures may result in inconsistent estimates, the analyst needs to exercise caution in applying these models. If the analyst' objective is to correct for the endogeneity of the two WTP responses, then the bivariate model proposed by Cameron and Quiggin [18] should suffice. Another advantage of the bivariate model in our context is that the Cameron-Quiggin version of our model (1) is simply a trivariate probit model, and the analyst can take advantage of standard statistical packages to estimate it.

Table 6 presents the results of the Cameron-Quiggin model, with incremental addition of treatment analogous to those in Table 3. The parameters of the two WTP equations are constrained to be identical for all three versions of the model.[15] The results follow essentially the same pattern as in Table 3 — with each addition of treatment, both the magnitude and significance of the self-protection variable in the WTP equation increases while the signs and significance levels on the other covariates are stable across these models. The likelihood ratio test rejects the null that correlation between the two WTP errors is zero at 5% significance level, which suggests that the estimated coefficients in the standard double-bound model may be somewhat biased. We note, however, that standard deviation of WTP estimates increases. This result seems consistent with Alberini [4], who finds that there is generally a trade-off between bias and efficiency of mean or median WTP estimates in making a choice between double-bound and bivariate specifications and that the double-bound model is often superior to the bivariate model in terms of efficiency of the WTP estimates. Nonetheless, all of our major results in the previous section are essentially intact with the bivariate model.

[Table 6][16]

B. Ordinal or Multinomial Self-protection Data

In some instances, analysts may wish to treat the categorical variable that describes self-protection as ordinal or multinomial data. Multinomial variable occurs naturally in practice, because consumers may take various types of protective actions and analysts often observe discrete responses

[15] We also ran a series of unconstrained versions of the model. The likelihood ratio tests, following Cameron and Quiggin [18], show that the constrained model is the most preferred specification.

[16] We used Stata program "mvprobit" developed by Cappellari and Jenkins [19]. Since the program utilizes the Geweke-Hajavassiliou-Kearne (GHK) estimator, the estimates are somewhat unstable and depend on the number of random draws, seed value, and data precision. We do not present the results as our main results for this reason.

(i.e. yes or no) for each type of actions. The ordered variable may also occur if the protective actions can be ordered to indicate the *level* of self-protection activity. For example, Gayer *et al.* [26] classify the distance of a residential house from hazardous waste sites into four ordered categories. Furthermore, multinomial data may be sometimes treated as ordinal data. For example, in our empirical example, there seems to be a natural order in the precautionary action level, as shown in Figure 1.

If we assume that s_i is generated in the ordinal manner, we use the following ordered probit structure: $s_i = m$ if and only if $\theta_{m-1} < s_i^* \leq \theta_m$ for some threshold θ_m where m indicates the m-th defensive option and $\theta_{-1} = -\infty$. The recursive endogenous structure in (1) is intact. For simplicity, we turn to the single-bound case. We can formulate the sample log-likelihood function.

$$\mathcal{L} = \sum_i \left[y_i \ln P_i^{ym} + (1 - y_i) \ln P_i^{nm} \right],$$

where

$$\begin{aligned}
P_i^{ym} &= \Pr(y_i = 1, s_i = m) = \Pr(y_i^* > t_i, \theta_{m-1} < s_i^* \leq \theta_m), \\
&= \Pr(y_i^* > t_i, s_i^* \leq \theta_m) - \Pr(y_i^* > t_i, \theta_{m-1} < s_i^*), \\
&= \int_{\nu_{1i}}^{\infty} \int_{\tau_{im-1}}^{\tau_{im}} \phi_2(z_{1i}, z_{2i}; \rho)\, dz_{2i} dz_{1i}, \\
&= \Phi_1(\tau_{im}) - \Phi_2(\nu_i, \tau_{im}; \rho) - \left[\Phi_1(\tau_{im-1}) - \Phi_2(\nu_i, \tau_{im-1}; \rho) \right],
\end{aligned}$$

$$\begin{aligned}
P_i^{nm} &= \Pr(y_i = 0, s_i = m) = \Pr(y_i^* < t_i, \theta_{m-1} < s_i^* \leq \theta_m), \\
&= \Pr(y_i^* \leq t_i, s_i^* \leq \theta_m) - \Pr(y_i^* \leq t_i, \theta_{m-1} < s_i^*), \\
&= \int_{-\infty}^{\nu_{1i}} \int_{\tau_{im-1}}^{\tau_{im}} \phi_2(z_{1i}, z_{2i}; \rho)\, dz_{2i} dz_{1i}, \\
&= \Phi_2(\nu_{1i}, \tau_{im}; \rho) - \Phi_2(\nu_{1i}, \tau_{im-1}; \rho),
\end{aligned}$$

where $\nu_{1i} = (t_i - X_{1i}\alpha_1 - s_i\beta_1)/\sigma_1$, $\tau_{im} = (\theta_m - X_2\beta_2)/\sigma_2$, Φ_1 is the standard normal CDF, and Φ_2 is the standard bivariate normal CDF. This log-likelihood function is a special case of Wu, Cook, and Strong [59]. If, instead, we treat s_i as multi-dimensional data, a multivariate probit model would be a natural choice. One potential problem with this approach is that the integral of a multivariate normal density does not have a closed-form expression, and thus integration needs to be performed numerically, which can be computationally demanding. Simulated maximum likelihood estimators such as the Geweke-Hajavassiliou-Kearne (GHK) estimator may be employed to reduce computational burden [29]. Since in our case, self-protection activities can be defined to be the ordered variable as Action, we present the results of the ordered bivariate probit model (with single-bound data only). We again observe the same pattern as in Table 3. The robustness of our results with these extensions increases confidence in our approach.

[Table 7]

7. Concluding Remarks

Existing literature has been silent as to how valuation analysts might estimate the welfare value of exogenous pollution risk reductions in the presence of heterogeneous consumers taking varying levels of self-protection activities. Previous studies have assumed that consumers are perfectly informed, and therefore, can optimize on self-protection activities — the assumption refutable by a number of empirical studies. This study takes into account both imperfect information and the dependence of welfare value on the self-protection choice, and proposes a general empirical strategy to estimate willingness-to-pay to avoid exogenous environmental risks. The goal is to estimate the welfare values from a sample distribution of respondents that *can be extrapolated into a population distribution*. Our approach is successfully applied to the case of the new arsenic rule for U.S. drinking water standards. With the distribution of our WTP estimates, which are shown to be decreasing in self-protection, we obtain a policy prescription that is qualitatively much different from that of the conventional WTP estimates.

Table 1. Arsenic Risk Perceptions
Before and After Information Provision

	R_0	R_1	R_0 - R_1	$\lvert R_0 - R_1 \rvert$
Mean	6.66	6.93	0.26	1.19
Std. Dev.	2.39	2.53	1.81	1.39
Percentile:				
10th	3	3	-2	0
25th	5	5	0	0
50th	7	8	0	1
75th	8	9	1	2
90th	10	10	3	3
Min	1	1	-5	0
Max	10	10	7	7
# of obs.	307	307	307	307

Note: R_0: An index from 1 to 10 that measures respondent's perception of arsenic risks in drinking water before giving information; R_1 = An index from 1 to 10 that measures perception of arsenic risks in drinking water after giving information.

Figure 1. Naive WTP Estimates and Precautionary Action Levels

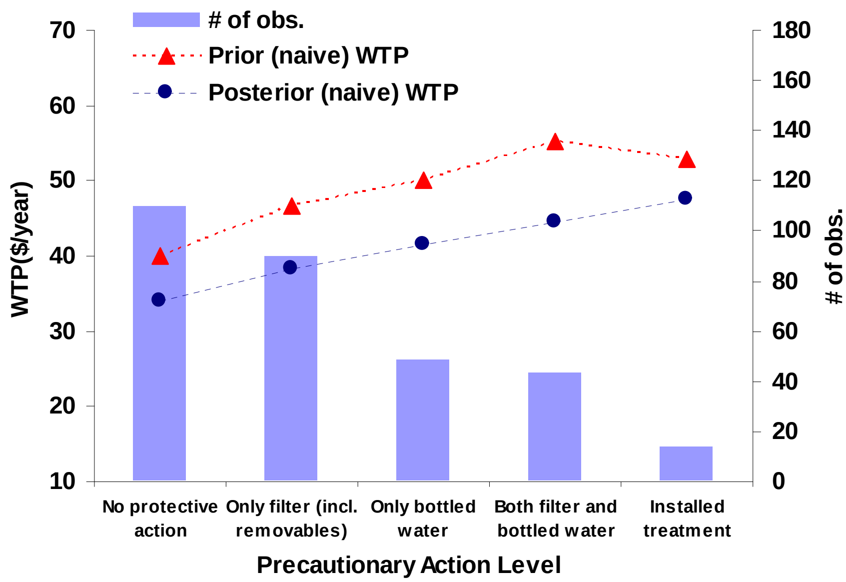


Table 2. Definition and Descriptive Statistics of Variables

Variables	Mean	Std. Dev.	Description
Protect	0.349	0.477	= 1 if respondent uses arsenic-related treatment or bottled water for drinking purpose
R_0	6.928	2.535	An index from 1 to 10 that measures respondent's perception of arsenic risks in drinking water before giving information: = 1 if very unsafe; = 10 if very safe
R_1	6.664	2.394	An index from 1 to 10 that measures respondent's perception of arsenic risks in drinking water after giving information: = 1 if very unsafe; = 10 if very safe
Age	53.922	16.007	Respondent's age
Sex	0.560	0.497	= 1 if male
Child	0.166	0.373	= 1 if there are children under 7 years of age in household
Edu	2.853	0.890	Education level: = 1 if eleventh grade or less; = 2 if high school diploma; = 3 if completed technical school or some college; = 4 if college graduate or more
Log(Y)	10.734	0.681	Logged annual household total income before tax
Taste	3.479	1.067	An index from 1 to 5 that measures respondent's perception about taste of drinking water
Odor	3.599	1.078	An index from 1 to 5 that measures respondent's perception about odor of drinking water
Color	3.691	1.053	An index from 1 to 5 that measures respondent's perception about color of drinking water

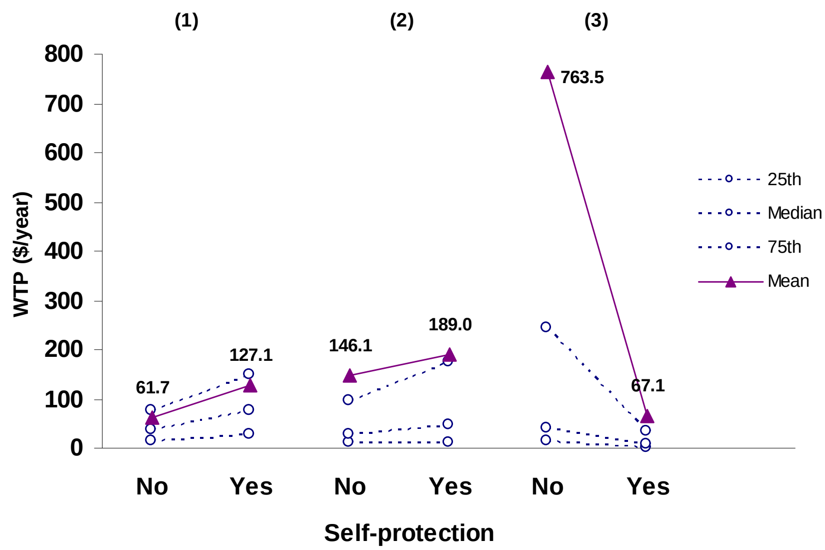
Table 3. Estimation Results

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
WTP equation						
Protect	-0.388	-1.301 †	-4.630 *	-0.267	-0.489 *	-1.058 *
R_0	-0.407 **			-0.158 ***		
R_1		-0.700 **	-0.959 **		-0.251 ***	-0.284 ***
Age	-0.026	-0.005	-0.020	-0.005	-0.003	-0.005
Sex	0.078	-0.235	-0.461	-0.040	-0.181	-0.218
Child	-0.308	0.748	0.630	-0.056	0.129	0.100
Edu	0.409	0.504	0.475	0.212 *	0.110	0.096
Log(Y)	0.628 ***	0.689 ***	1.051 **	0.414 ***	0.490 ***	0.547 ***
Self-protection equation						
R_0	-0.169 ***	-0.169 ***	-0.158 ***	-0.169 ***	-0.169 ***	-0.165 ***
Taste	-0.271 **	-0.271 **	-0.321 ***	-0.271 **	-0.271 **	-0.285 **
Odor	-0.132	-0.132	-0.159	-0.132	-0.132	-0.141
Color	0.044	0.044	0.106	0.044	0.044	0.054
Age	-0.008	-0.008	-0.009 †	-0.008	-0.008	-0.008
Sex	-0.098	-0.098	-0.114	-0.098	-0.098	-0.098
Child	-0.102	-0.102	-0.102	-0.102	-0.102	-0.095
Edu	-0.107	-0.107	-0.108	-0.107	-0.107	-0.109
Log(Y)	0.254 ***	0.254 ***	0.255 ***	0.254 ***	0.254 ***	0.256 ***
ρ_{ws}	0.000	0.000	0.484 *	0.000	0.000	0.231
# of obs.	307	307	307	307	307	307
Log-likelihood	-350.887	-346.115	-344.227	-575.893	-552.653	-552.151
Risk information		√	√		√	√
Endogenous self-protection			√			√
Follow-up data				√	√	√
Mean WTP	84.5	161.1	520.8	53.0	47.5	50.7
(Std. Dev.)	121.8	355.0	1931.1	26.9	34.4	43.1
Median WTP	41.9	20.7	22.9	38.5	29.1	30.2

Note: †, *, **, and *** indicate significance at 15%, 10%, 5%, and 1% levels.

Figure 2. WTP Estimates and Self-Protection

(a) Single-Bound Models



(b) Double-Bound Models

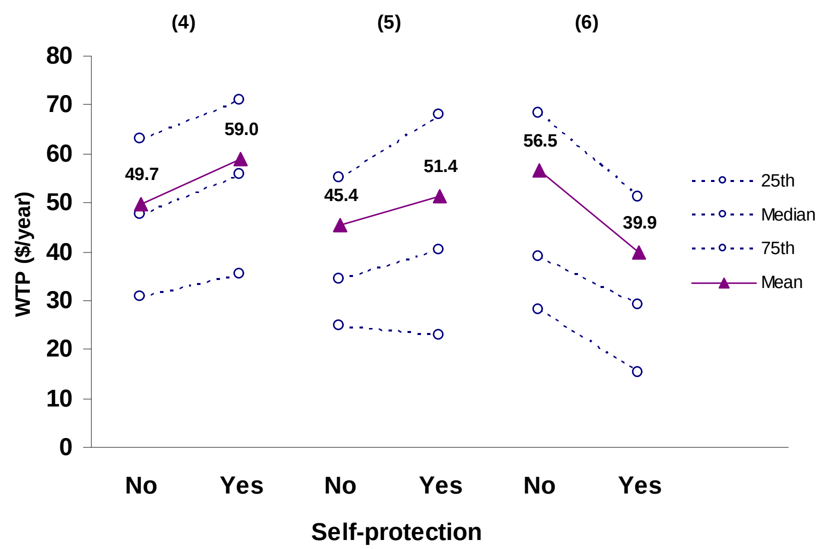


Table 4. Estimated Percents of "Winners" from New Arsenic Rule

	Single-bound			Double-bound		
	(1)	(2)	(3)	(4)	(5)	(6)
Percents of winners from the rule						
No protection	44.5%	41.0%	50.5%	62.0%	40.0%	49.0%
Self-protect	68.2%	53.3%	23.4%	72.0%	50.5%	20.0%
Total	52.8%	45.3%	41.0%	65.5%	43.6%	45.0%
Risk information		√	√		√	√
Endogenous self-protection			√			√
Follow-up data				√	√	√

Table 5. Welfare Values of New Arsenic Rule with Information Dissemination

		New rule only	New rule & information program				
	Obs.	WTP	Predicted effect on self-protection		V^{Info}	V^{Rule}	V^{Total}
			No	Yes			
Currently protected:							
No	200	$56.50	179	21	$7.39	$49.73	$57.13
Yes	107	$39.87	61	46	-$24.00	$67.13	$43.13
Total	307	$50.70	240	67	-$3.55	$55.79	$52.25

Figure 3. Distribution of Welfare Values of Two Alternative Policies

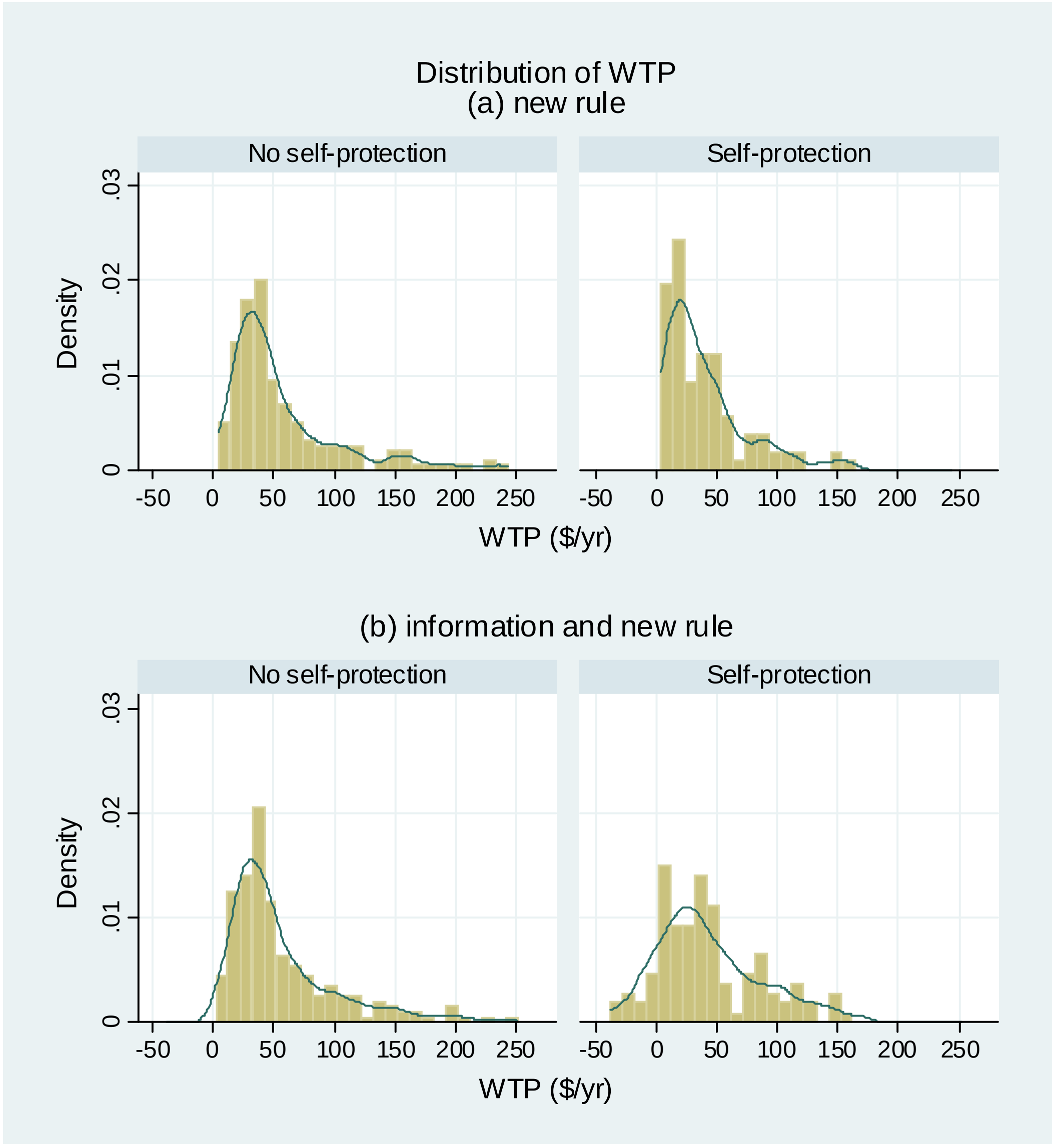


Table 6. Estimation Results of the Cameron-Quiggin Model

Independent variables	(7)	(8)	(9)
WTP equation			
Protect	-0.525	-1.051 *	-4.126 **
R_0	-0.339 ***		
R_1		-0.582 ***	-0.855 ***
Age	-0.029 *	-0.023	-0.039
Sex	-0.002	-0.256	-0.456
Child	-0.378	0.036	-0.159
Edu	0.490	0.212	0.144
Log(Y)	0.554 ***	0.758 ***	1.133 ***
Self-protection equation			
R_0	-0.169 ***	-0.169 ***	-0.153 ***
Taste	-0.271 **	-0.271 **	-0.303 **
Odor	-0.132	-0.132	-0.160
Color	0.044	0.044	0.079
Age	-0.008	-0.008	-0.009
Sex	-0.098	-0.098	-0.102
Child	-0.102	-0.102	-0.120
Edu	-0.107	-0.107	-0.114
Log(Y)	0.254 ***	0.254 ***	0.255 ***
$\rho_{w1,w2}$	0.382 **	0.382 **	0.528 ***
$\rho_{w1,s}$			0.444 ***
$\rho_{w2,s}$			0.356 **
# of obs.	307	307	307
Log-likelihood	-547.302	-532.603	-532.576
Risk information		√	√
Endogenous self-protection			√
Correlated WTP responses	√	√	√
Mean WTP	51.8	64.9	221.4
(Std. Dev.)	65.6	116.8	661.3
Median WTP	31.4	16.1	17.7

Note: †, *, **, and *** indicate significance at 15%, 10%, 5%, and 1% levels.

Table 7. Estimation Results of the Ordinal Self-protection Model

Independent variables	(10)	(11)	(12)
WTP equation			
Action	-0.388	-1.301 †	1.773 *
R_0	-0.407 **		
R_1		-0.700 **	0.913 **
Age	-0.026	-0.005	0.009
Sex	0.078	-0.235	0.351
Child	-0.308	0.748	-1.206
Edu	0.409	0.504	-0.526
Log(Y)	0.628 ***	0.689 ***	-1.159 **
Precautionary action			
R_0	-0.133 ***	-0.133 ***	-0.129 ***
Taste	-0.256 ***	-0.256 ***	-0.293 ***
Odor	-0.024	-0.024	-0.049
Color	-0.025	-0.025	0.041
Age	-0.001	-0.001	0.000
Sex	0.028	0.028	0.004
Child	0.248	0.248	0.252
Edu	-0.026	-0.026	-0.030
Log(Y)	0.250 **	0.250 **	0.322 ***
ρ_{ws}	0.000	0.000	0.425 **
# of obs.	307	307	307
Log-likelihood	-594.265	-589.493	-588.463
Risk information		√	√
Endogenous self-protection			√
Follow-up data			
Ordinal self-protection	√	√	√
Mean WTP	84.5	161.1	353.5
(Std. Dev.)	121.8	355.0	1050.0
Median WTP	41.9	20.7	26.4

Note: †, *, **, and *** indicate significance at 15%, 10%, 5%, and 1% levels. Action = 1 if a respondent takes no precautionary action, = 2 if uses filter or removable treatment only, = 3 if uses bottled water only, = 4 if uses both filter and bottled water but not installed treatment, and = 5 if uses installed treatment.

Appendix. Robustness of Double-Bound Estimation with Endogenous Self-selection

Independent variables	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)
WTP equation						
Protect	-1.058 *	-0.934 †	-1.038 *	-1.062 *	-1.050 *	-0.913 †
R_1	-0.284 ***	-0.228 ***	-0.287 ***	-0.282 ***	-0.284 ***	-0.225 ***
ArsenicCurr		0.043 **				0.047 **
ArsenicHist		0.020 *				0.022 *
Size_M			0.118		0.079	0.042
Size_L			0.142		0.089	0.277
Age	-0.005	-0.007	-0.005		0.000	
Age 40 to 49				0.448	0.424	0.333
Age 50 to 59				0.016	0.000	-0.033
Age 60 or above				-0.166	-0.182	-0.297
Sex	-0.218	-0.199	-0.217	-0.206	-0.205	-0.215
Child	0.100	0.072	0.083	0.150	0.131	0.085
Edu	0.096	0.076	0.098	0.092	0.094	0.074
Log(Y)	0.547 ***	0.460 ***	0.540 ***	0.517 ***	0.514 ***	0.411 ***
Self-protection equation						
R_0	-0.165 ***	-0.165 ***	-0.165 ***	-0.166 ***	-0.166 ***	-0.166 ***
Taste	-0.285 **	-0.283 **	-0.286 **	-0.277 **	-0.277 **	-0.275 **
Odor	-0.141	-0.137	-0.141	-0.152	-0.152	-0.148
Color	0.054	0.049	0.055	0.046	0.047	0.042
Age	-0.095	-0.008	-0.008			
Age 40 to 49				0.041	0.041	0.046
Age 50 to 59				-0.109	-0.109	-0.107
Age 60 or above				-0.216	-0.216	-0.215
Sex	-0.008	-0.098	-0.099	-0.097	-0.097	-0.097
Child	-0.098	-0.093	-0.095	-0.025	-0.025	-0.023
Edu	-0.109	-0.108	-0.109	-0.089	-0.089	-0.088
Log(Y)	0.256 ***	0.255 ***	0.256 ***	0.221 ***	0.221 ***	0.220 ***
ρ	0.231	0.214	0.222	0.223	0.218	0.186
# of observations	307	307	307	307	307	307
Log-likelihood	-552.15	-547.22	-552.01	-550.95	-550.89	-545.37

Note: †, *, **, and *** indicate significance at 15%, 10%, 5%, and 1% levels. ArsenicCurr = average arsenic concentrations in μg/L in 2006. ArsenicHist = average arsenic concentrations in μg/L during 2000-05. Size_M = 1 if the population of community is more than 500 but less than 1000. Size_L = 1 if the population of community is more than 1000. Age dummies = 1 if respondent's age is in the range. Other variables are defined in Table 2.

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