Modeling Certainty-Adjusted Willingness to Pay for Ecosystem Service Improvement from Agriculture

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Abstract:

The public demand for ecosystem services measured by willingness to pay (WTP) in contingent valuation studies provides important information for designing Payment-for-Ecosystem-Service (PES) programs. However, the hypothetical markets for contingent valuation and respondents' unfamiliarity with certain ecosystem services may increase their preference uncertainty, which may increase variance and even cause bias in WTP estimates. Taking advantage of a unique stated preference data set that includes a follow-up question rating the respondent's certainty level, this study evaluates alternative methods of modeling certainty-adjusted WTP for cleaner lakes and abated global warming. Results suggest that the incorporation of self-reported uncertainty into binary choice models significantly reduces the median WTP and appears to improve our understanding of the demand for ecosystem services.

Keywords:

Contingent valuation, Willingness to Pay**,** Preference Uncertainty,
Numerical certainty scale, Ecosystem services

JEL Codes:

Q51, Q57

1 Introduction

The public demand for nonmarket ecosystem services (ES) stems from people's desire for a better environment for living, such as clean air and drinking water for health, abundant natural resources for recreation, and diverse landscapes for scenic views. A broad variety of environmental improvements that would affect the welfare of local communities and the general public can be generated from land management practices in agricultural ecosystems. Examples include water quality improvement from less fertilizer input, and greenhouse gas (GHG) mitigation from winter cover crops. Payment-for-Ecosystem-Service (PES) programs have been increasingly implemented around the world to facilitate the provision of these ecosystem services (ES). In order to design efficient public policies for enhancing ecosystem services from agriculture, the demand for ES needs to be addressed in addition to the supply side analysis on farmers. The public willingness to pay (WTP) in contingent valuation studies provides important measure for the ES demand.

However, the survey-based contingent valuation is likely to suffer from the *hypothetical bias*, which is defined as "the potential error induced by not confronting the individual with an actual situation" (Schulze, et al., 1981). Hypothetical bias may increase respondents' preference uncertainty, which would increase variance and even cause bias in the estimation of WTP. The valuation of ecosystem services, which are public goods, would lead to even larger hypothetical bias than valuation of private goods (List and Gallet, 2001). Based on the literature review, hypothetical bias possibly originates from the following four sources:

First, respondents may state a higher payment level than what they would actually pay as they are not required to make it under hypothetical scenarios (Loomis and Ekstrand, 1998).

Second, uncertain responses can be caused by incomplete knowledge of the hypothetical markets (Li and Mattsson, 1995). The good or service to be valued may be unclear to respondents who have never experienced or used it, such as mitigation of greenhouse gas emissions. For tangible goods or services, the result of changes in quality/quantity may not be fully understood (Wang and Whittington, 2005). For example, the degree of improvement in eutrophic lakes may be unclear to some people.

Third, respondents may have different understanding of the proposed policy instrument for providing the good (Shaikh, et al., 2007), such as how an increased income tax would serve as a payment vehicle to collect public funding.

Fourth, individuals may also have specific uncertainties in their evaluation of trade-off between amenity and dollar values (Shaikh, et al., 2007), perception of substitutes for the hypothetical goods, or expectation of future income (Wang and Whittington, 2005).

Given the potential for hypothetical bias and preference uncertainty in willingness to pay estimation, ES demand estimates should be tested and, if necessary, adjusted accordingly. Champ et al. (2009) compared different methods to mitigate hypothetical bias and concluded that the contingent valuation (CV) treatment with a follow-up certainty question would produce both consistent WTP estimates and response distributions that are similar to the actual treatment. Taking advantage of a unique stated preference data set that includes a follow-up question rating the respondent's certainty level, this study evaluates alternative methods of modeling certainty-adjusted WTP for two important ecosystem services from agriculture-- improvement in eutrophic lakes and abated global warming.

Previous studies have used various ways to incorporate preference uncertainty into contingent valuation. In the case of binary choice format with a follow-up 10-point numerical certainty scale, “yes” and “no” responses were recoded to a grid of probability ranging from 0 to 1 (Chang, et al., 2007, Li and Mattsson, 1995, Loomis and Ekstrand, 1998, Shaikh, et al., 2007). Alternatively, “no” responses were recoded as “yes” based on a fixed cutoff level of certainty (Champ and Bishop, 2001, Champ, et al., 1997, Ethier, et al., 2000, Loomis and Ekstrand, 1998, Samnaliev, et al., 2006). In the case of a polychotomous choice format with uncertain choices such as “probably yes”, “not sure”, and “probably no”, the responses were analyzed directly (Lundhede, et al., 2009, Wang and Whittington, 2005), or re-categorized to binary responses under different assumptions (Chang, et al., 2007, Johannesson, et al., 1998, Samnaliev, et al., 2006, Vossler, et al., 2003, Whitehead, et al., 1998). There are also other unique attempts to model the preference uncertainty. For example, Li and Mattsson (1995) treated respondent uncertainty as one source of measurement error and weighted the individual dichotomous-choice responses directly in the likelihood function by the numerical certainty scale. Van Kooten et al. (2001) introduced a fuzzy model that assumes two fuzzy sets for willingness to pay and willingness not to pay. This model was then extended to a fuzzy random utility maximization framework by Sun and van Kooten (2009). Wang and Whittington (2005) developed a non-econometric approach relying on the stochastic payment card for modeling preference uncertainty. Moore et al. (2010)

assumed that the certainty scale embodied a flexible mapping between the probability of payment and the integers 1-10, and applied maximum likelihood estimation (MLE) to obtain the parameters of a mapping rule for a specific dataset.

Examples of goods and services that have been valued with preference uncertainty include conservation of a lagoon (Chang, et al., 2007, Whitehead, et al., 1998), private access to public land (Samnaliev, et al., 2006, Vossler, et al., 2003), green energy (Champ and Bishop, 2001, Ethier, et al., 2000, Poe, et al., 2002), and endangered species (Loomis and Ekstrand, 1998).

Compared to previous studies, this paper complements the literature in two ways. First, we extend the regime of preference uncertainty estimation to ecosystem services from agriculture, which include a global public good, greenhouse gas mitigation and a regional public good, eutrophic lake reduction. Second, we compare four calibration methods to incorporate numerical certainty into a two-stage dichotomous choice model, which accounts for both the prior probability of having a positive WTP and the magnitude of the conditional WTP. In the process, we apply panel data methods to models that symmetrically or asymmetrically recode binary responses into a grid of probability based on 10-point certainty scale (Chang, et al., 2007, Loomis and Ekstrand, 1998, Shaikh, et al., 2007).

2 Theoretical model

Resident demand for nonmarket ecosystem services is assumed to be rooted in the individual utility model (Flores, 2003). That model holds that utility depends on a bundle of market goods, *Z*, the level of environmental improvements, *ES*, and is conditioned on resident-specific characteristics, *R*, such as age, education, gender and voter registration. Residents choose the level of market goods to maximize utility subject to a budget constraint that the expenditure cannot exceed income *y*, given price vector P_z.

$$\underset{Z}{Max} U^R\left(Z^R, ES(lake, GHG) \mid R\right) \tag{1}$$

$$s.t.\ P_Z Z^R \leq y \text{ and } ES \leq ES^0 \tag{2}$$

The demand function for market good is

$$Z^{R*} = Z\left(P_Z, ES, y \mid R\right) \tag{3}$$

The indirect utility function at the optimal level of the market good bundle is

$$U^{R*}\left(Z^{R*}, ES \mid R\right) = V\left(P_Z, ES, y \mid R\right) \tag{4}$$

At the status quo level of ecosystem services, the indirect utility can be written as

$$V\left(P_Z, ES^0, y \mid R\right) \tag{5}$$

If there is an improvement in ecosystem services from ES^0 to ES^1, such as reduction in eutrophic lakes and greenhouse gas emissions, then the individual would be willing to give up a certain amount of income, known as willingness to pay (WTP), such that:

$$V^0\left(P_Z, ES^0, y \mid R\right) = V^1\left(P_Z, ES^1, y - WTP \mid R\right) \tag{6}$$

The true WTP can be solved as a function of those characteristics in the indirect utility function $WTP\left(P_Z, ES^0, ES^1, y \mid R\right)$. However, for each individual, the observed WTP is comprised by the true willingness to pay, WTP_i*, and an error term ε_i, which represent stochastic disturbances that are not captured by the indirect utility function.

$$WTP_i = WTP_i^*\left(P_Z, ES^0, ES^1, y \mid R\right) + \varepsilon_i \tag{7}$$

In an ordinary contingent valuation study, the error term, which has a normal distribution with zero mean and constant variance, is assumed to reflect the observer uncertainty arising from omitted variables. However, the stochastic disturbance is also related to the respondent from their inherent randomness in preferences (Li and Mattsson, 1995). For the dichotomous choice question, the respondent's one-shot response is a realization of the underlying probabilistic mechanism because they may not give the same response each time when facing the same conditions. Li and Mattsson (1995) showed that the maximum likelihood estimate of the valuation distribution incorporating both observer uncertainty and respondent uncertainty would be flattened compared with the true distribution. The associated overestimation of the standard deviation may lead to value inference bias, although the parameter vector is still consistent. Different approaches to capture and model this preference uncertainty are discussed in sections 3 and 4.

In dichotomous-choice contingent valuation surveys, respondents are typically asked to vote "yes" or "no" for a payment level associated with an improvement in the quality of non-market goods. They would vote "yes" if WTP is greater than the given program cost *C* as shown in equation 8.

$$\begin{aligned}\Pr(yes_i) &= \Pr\left(V^1\left(ES^1, y_i - C_i\right) > V^0\left(ES^0, y_i\right)\right) \\ &= \Pr\left(V^1\left(ES^1, y_i - C_i\right) > V^1\left(ES^0, y_i - WTP_i\right)\right) = \Pr\left(WTP_i > C_i\right)\end{aligned} \tag{8}$$

As pointed out by Wang (1997), an individual's valuation of any good or service is best characterized as a random variable with an unspecified probability. Such a probability can be represented by the probability of voting "yes" in equation 8. An example probability distribution is illustrated in Figure 1. Normally, if the mean of WTP is greater than proposed tax payment (C), the respondent would vote "yes". When considering preference uncertainty, the decision rule depends on the whole distribution rather than the mean. The variance of distribution reflects both observer uncertainty and respondent uncertainty. The shade area that is below the function and greater than the proposed tax payment represents the probability of voting “yes” in empirical estimation.

Following Chen (2010), this study adopts a spike probability model to distinguish people who have zero willingness to pay for the ecosystem services and are not responsive to price change. The unconditional probability of voting “yes” to the program is a product of the probability positive WTP and the conditional probability of “yes” vote as in equation 9.

$$\Pr(yes_i \mid WTP_i) = \Pr\left(WTP_i > 0\right)\Pr\left(yes_i \mid WTP_i > 0\right) \tag{9}$$

The probability of having positive willingness is endogenously modeled with environmental quality changes and individual characteristics.

3 Data

Data for this study come from a 2009 mail survey of Michigan residents that yielded 2211 responses (40% response rate). The contingent valuation (CV) question was posed as a dichotomous choice referendum with income taxes as the payment vehicle. Each respondent was asked to vote on three independent land stewardship programs, which provide different greenhouse gas and eutrophic lake reductions from changes in land management practices associated with a tax payment. If more than 50% of the voters voted on the program, it would be implemented and they would have to pay the cost.

The reductions in eutrophic lake numbers and greenhouse gas emissions were selected among a series of environmental improvements from agriculture because of their significant and measurable impact on the public based on both an ES quantification study and a survey pretest (Chen, 2010). The basic values of the two environmental improvements were in five levels: zero change, low change, median change, high change and double the high change[1] of the maximum possible reduction calculated by Chen (2010).

The cost for each program was expressed as the respondent's own share of increased annual federal income tax, which would only be used in Michigan. The costs for all three land stewardship programs were the same to each respondent but were varied across residents. Based on the questionnaire pretest, the program cost levels were set at \$10, \$30, \$50, \$100, and \$200 per year. If the respondent voted "no" for the WTP question, a follow-up question asked whether she would vote for the program if it did not cost her anything. That response is then used to identify respondents who have zero WTP.

To test the effect of provision mechanisms on respondents' WTP, two alternative versions of the questionnaire were provided. One specified that the land stewardship program was to pay *farmers* to adopt environmental friendly farming practices, while the other was to pay *general land owners*.

To capture the individual preference uncertainty, several formats have been used in the literature. The simplest format is to add a "not sure" or "don't know" option to the dichotomous "yes/no" choice to a given price (Balcombe and Fraser, 2009, Fenichel, et al., 2006, Haener and Adamowicz, 1998, Krosnick, et al., 2002, Wang, 1997). A similar but extended format is the polychotomous choice (PC) method, in which respondents are

[1] In pretest interviews in the contingent valuation survey, some respondents reported that the ecosystem service changes were too small although they still passed the scope test. To reduce the probability of scope insensitivity problem, we doubled the original maximum change as the new range of the two attributes.

provided with a set of uncertainty options, for example, “definitely yes”, “probably yes”, “not sure”, “probably no”, and “definitely no” (Alberini, et al., 2003, Chang, et al., 2007, Johannesson, et al., 1998, Samnaliev, et al., 2006, Vossler, et al., 2003, Whitehead, et al., 1998). The third way is to follow the standard “yes/no” choice by a numerical certainty scale (NCS) ranging from 1 to 10, with which the respondents can indicate the level of certainty about their “yes/no” voting decision (Champ and Bishop, 2001, Champ, et al., 1997, Chang, et al., 2007, Ethier, et al., 2000, Li and Mattsson, 1995, Loomis and Ekstrand, 1998, Moore, et al., 2010, Poe, et al., 2002, Samnaliev, et al., 2006, Shaikh, et al., 2007). A fourth approach that directly elicits the distribution of preference uncertainty is the stochastic payment card (SPC) format, which presents each respondent with numerical likelihood that the she would vote “yes” to a series of payment levels (Ichoku, et al., 2009, Wang and Whittington, 2005).

Among those formats for eliciting preference uncertainty, this study adopted the 10-point numerical certainty scale approach in a follow-up question, which asked how certain the respondents were with their “yes/no” answers to the WTP question. The survey question is shown in Figure 2.

Fourteen questionnaire versions were generated from an experimental design with three CV questions per respondent. Information about eutrophication of lakes and global warming (GW), how residents would be affected and how land management practices would improve environmental qualities were also provided in the survey. Residents’ responses to those information, their attitudes on various environmental issues, and demographic status were also collected from the survey. Detailed information about data collection and questionnaire design can be found in Chen (2010).

4 Empirical model and variables

4.1 Econometric model of WTP

The model for empirical estimation conforms to the conceptual model of contingent valuation with a spike for zero WTP. Following Chen (2010), the spike probability of positive WTP for individual *i* is a function of the change in ecosystem services *ES*, and individual characteristics R_i. The reductions in eutrophic lakes and greenhouse gas emission are indexed by *j* for the *ES* variable.

$$\Pr\left(WTP_i > 0\right) = \Phi\left(a + bES_j + cR_i\right) \tag{10}$$

As respondents who have a zero WTP have been separated by the spike model, the WTP from the rest of respondents is strictly positive, which is then ensured by the exponential functional form in equation 11. *ES* still represents the change in the number of eutrophic lakes and tons of greenhouse gas emission. *A* is respondent's attitude towards global warming. *R* indicates individual-specific characteristics. An interaction of concern about global warming and greenhouse gas reduction is generated to test the aggregate effect.

$$WTP_i \,|_{WTP_i>0} = \exp\left(\delta + \beta ES_j + \alpha A_i + \varphi ES_{ghg} A_i + \gamma R_i + \varepsilon_{ij}\right) \tag{11}$$

Assuming the error term ε is normally distributed with mean zero and constant variance σ^2, the conditional probability distribution of voting "yes" to the dichotomous-choice valuation question with cost C_i is

$$\begin{aligned}
\Pr(Y_i = 1|_{WTP_i > 0}) &= \Pr\left(WTP_i > C_i\right) \\
&= \Pr\left(\exp\left(\delta + \beta ES_j + \alpha A_i + \varphi ES_{ghg} A_i + \gamma R_i + \varepsilon_{ij}\right) > C_i\right) \\
&= \Pr\left(\delta + \beta ES_j + \alpha A_i + \varphi ES_{ghg} A_i + \gamma R_i + \varepsilon_{ij} > \ln C_i\right) \\
&= \Pr\left(\frac{\delta - \ln C_i + \beta ES_j + \alpha A_i + \varphi ES_{ghg} A_i + \gamma R_i}{\sigma} > -\frac{\varepsilon_{ij}}{\sigma}\right) \\
&= \Phi\left(\frac{\delta}{\sigma} - \frac{1}{\sigma}\ln C_i + \frac{\beta}{\sigma} ES_j + \frac{\alpha}{\sigma} A_i + \frac{\varphi}{\sigma} ES_{ghg} A_i + \frac{\gamma}{\sigma} R_i\right)
\end{aligned} \tag{2.12}$$

The unconditional probability of voting "yes" is:

$$\begin{aligned}
\Pr(Y_i = 1) &= \Pr\left(WTP_i > 0\right)\Pr\left(Y = 1_i \mid WTP_i > 0\right) \\
&= \left[1 - \Phi\left(a + bES_j + cR_i\right)\right]\Phi\left(\frac{\delta}{\sigma} - \frac{1}{\sigma}\ln C_i + \frac{\beta}{\sigma} ES_j + \frac{\alpha}{\sigma} A_i + \frac{\varphi}{\sigma} ES_{ghg} A_i + \frac{\gamma}{\sigma} R_i\right)
\end{aligned} \tag{2.13}$$

The first term represents the probability of having positive WTP. The second term represents the payment level conditional on willingness to pay a positive amount for the environmental improvements. Since we assume the two decisions are independent, the probability of zero WTP and a positive amount of WTP can be estimated separately. As the response to the zero WTP question is binary and the probability is assumed to follow a normal distribution, standard probit regression can be applied to the spike model. Since each respondent was presented with three independent alternative programs, random effect probit is used to account for the correlation among the three decisions made by the same respondent.

4.2 Methods for incorporating preference uncertainty

For the conditional probability of positive WTP, conventional dichotomous-choice CV studies employ binary response models, such as probit or logit. In this paper, we calibrate the dichotomous response by numerical certainty scale from a follow-up question and adopt following econometric models to estimate the adjusted WTP.

- **Probit model with different fixed cutoff certainty levels**

With the 10-point numerical certainty scale, the dichotomous choice regarding program participation at a given price can be recoded based on an arbitrarily chosen cutoff level of certainty. The binary "yes" response (Y_i=1) is recoded as "no" (Y_i=0) if the respondent's certainty is less than a specific cutoff level. Four cutoff levels are considered, at 10, 9, 8 and 7, as shown in Table 1. The adjusted responses are then used in the standard random effect probit model. In this paper, the cutoff point is set at 7 when comparing results with other methods.

- **Ordered probit model with polychotomous response**

The binary responses are recoded as "yes" (Y_i=1), "indifferent" (Y_i=0.5) and "no" (Y_i=0) depending on a cutoff level of certainty as shown in Table 2. The cutoff certainty level is set at 7, so answers of "yes" or "no" with certainty values of 7 or higher are coded as Y_i=1 or Y_i=0. Certainty levels of 6 or lower are coded Y_i=0.5 for "uncertain."

The adjusted responses are then estimated by ordered probit with the following log-likelihood function, where δ_i and η_i are unknown cut points.

$$\begin{aligned}\log L = &\sum_{Y_i=2} \log\left[1-\Phi\left(\frac{\ln C_i + \delta_i - \beta ES_j - \alpha A_i - \varphi ES_{ghg} A_i - \gamma R_i}{\sigma}\right)\right] \\ &+\sum_{Y_i=1} \log\left[\Phi\left(\frac{\ln C_i + \delta_i - \beta ES_j - \alpha A_i - \varphi ES_{ghg} A_i - \gamma R_i}{\sigma}\right)\right. \\ &\left.-\Phi\left(\frac{\ln C_i - \eta_i - \beta ES_j - \alpha A_i - \varphi ES_{ghg} A_i - \gamma R_i}{\sigma}\right)\right] \\ &+\sum_{Y_i=0} \log\left[\Phi\left(\frac{\ln C_i - \eta_i - \beta ES_j - \alpha A_i - \varphi ES_{ghg} A_i - \gamma R_i}{\sigma}\right)\right]\end{aligned} \quad (14)$$

- **Symmetric/ Asymmetric uncertainty model**

The original responses are recoded as probability of “yes” by combining the certainty score with dichotomous choices. Different recoding approaches have been applied in previous studies (Chang, et al., 2007, Li and Mattsson, 1995, Loomis and Ekstrand, 1998, Shaikh, et al., 2007). Li and Mattsson (1995) coded a 60% certainty level following “yes” response as 0.6, while a 60% certainty level following “no” response was coded as 1−0.6=0.4. Loomis and Ekstrand (1998) criticized this coding scheme as it altered the original “yes” or “no” choice made by the respondent. Instead, they implemented a slightly different numerical certainty scale to separate “yes” and “no” response as shown in Figure 3, where 0 and 1 indicate the most certain extremes of the “no” and “yes” responses respectively, and 0.5 indicates uncertainty of either response. They and others have adopted logit models to estimate the recoded data by transforming the dependent variable as $\log\left[\Pr(Yes)/(1-\Pr(Yes))\right]$ (Chang, et al., 2007, Loomis and Ekstrand, 1998, Shaikh, et al., 2007). When both “yes” and “no” responses are recoded, the method is referred as the Symmetric Uncertainty Model (SUM). The Asymmetric Uncertainty Model (ASUM) refers to the case when only “yes” responses are recoded.

This paper also applies the SUM and ASUM methods, but with a different coding scheme and econometric models. For the Symmetric Uncertainty Model, the binary responses are recoded as continuous responses ranging from 0 to 1 depending on the level of certainty. If a respondent voted “yes”, the lowest probability for her to pay is 0.5. As shown in Table 3, each one point increase in the certainty level adds 0.05 to 0.5, so a “yes” response with certainty of 1 gives a probability of 0.55 and whereas a “yes” with a certainty of 10 gives a probability of “1”. Similarly, the “no” responses are recoded from a highly certain 0 to a very uncertain 0.45 in response to certainty levels 10 to 1. For the Asymmetric Uncertainty Model, only "yes" responses are recoded while "no" is left as zero probability. The details of calibration are shown in Table 3. Figures 4 and 5 display the percentage of binary responses and certainty-adjusted responses under SUM method in the survey sample.

The probability of these adjusted responses can be estimated using a fractional binary response models, such as fractional probit. Since Pr$(Y_i=1|_{WTP>0})$ is normally distributed in [0,1], nonlinear least squares (NLS) can be used to consistently estimate the model. However, NLS is unlikely to be efficient because common distributions for a fractional response imply heteroskedasticity. Thus, a quasi-MLE approach can be a good alternative to consistently estimate model parameters (Wooldridge, 2010). The log-likelihood function is as follows:

$$\begin{aligned} \log L = \sum_{i}^{N} \Big\{ & \left[1-\Pr(Y_i=1|_{WTP_i>0})\right] \cdot \\ & \log\left[1-\Phi\left(\frac{\delta}{\sigma}-\frac{1}{\sigma}\ln C_i+\frac{\beta}{\sigma}ES_j+\frac{\alpha}{\sigma}A_i+\frac{\varphi}{\sigma}ES_{ghg}A_i+\frac{\gamma}{\sigma}R_i\right)\right]+ \\ & \Pr(Y_i=1|_{WTP_i>0})\log\left[\Phi\left(\frac{\delta}{\sigma}-\frac{1}{\sigma}\ln C_i+\frac{\beta}{\sigma}ES_j+\frac{\alpha}{\sigma}A_i+\frac{\varphi}{\sigma}ES_{ghg}A_i+\frac{\gamma}{\sigma}R_i\right)\right]\Big\} \end{aligned} \tag{15}$$

A panel data structure should be imposed on the model due to correlation among multiple choices made by each respondent. The common random effects approach, which attempts to obtain a joint distribution and to integrate out unobserved heterogeneity, is computationally demanding and would require additional assumptions on distribution. The generalized estimating equations (GEE) method with a specified correlation matrix provides a tractable solution (Wooldridge, 2010) that we estimate using STATA 10.1.

4.3 Welfare estimation

In order to compare different econometric specifications that incorporate preference uncertainty, the mean WTP, median WTP and efficiency of WTP estimation are calculated for these certainty-adjusted models and the conventional dichotomous-choice CV model.

The mean and median willingness to pay conditional on WTP greater than zero are

$$E(WTP_i|_{WTP_i>0}) = \exp\left(\delta + \beta ES_j + \alpha A_i + \varphi ES_{ghg} A_i + \gamma R_i + \frac{\sigma^2}{2}\right) \tag{16}$$

$$Median(WTP_i|_{WTP_i>0}) = \exp\left(\delta + \beta ES_j + \alpha A_i + \varphi ES_{ghg} A_i + \gamma R_i\right) \tag{17}$$

Since the exponential function of WTP typically has a fat tail and may lead to extremely large mean values, we compute and compare the median WTP across different methods.

The unconditional median willingness to pay is

$$\begin{aligned} Median(WTP_i) &= \Pr\left(WTP > 0\right) \cdot Median(WTP_i|_{WTP_i>0}) \\ &= \left[\Phi\left(a + bES_j + cR_i\right)\right] \cdot \exp\left(\delta + \beta ES_j + \alpha A_i + \varphi ES_{ghg} A_i + \gamma R_i\right) \end{aligned} \tag{18}$$

The efficiency of WTP estimation is measured by comparing the relative variability around the median WTP using equation 19, where CI_U and CI_L are upper and lower bounds of a 95% confidence interval (Loomis and Ekstrand, 1998).

$$\text{EF } (WTP) = (CI_U – CI_L) \text{ / Median } (WTP) \tag{19}$$

Based on a review by Akter et al. (2008), empirical evidence indicated that various certainty measurements and calibration techniques generate inconsistent welfare estimates in terms of value and efficiency, though it is expected that the certainty-adjusted WTP estimate should be lower and more efficient than the conventional WTP.

The median spike probability and conditional WTP are calculated for each respondent using individual-specific values for attributes that are significant at 90% level. The conditional WTP, unconditional WTP and their confidence intervals in the entire sample are estimated by bootstrapping the mean from individual median WTPs with 500 replications.

4.4 Preference certainty model

To explore the determinants of certainty in respondents' willingness-to-pay decisions, the 10-point numerical certainty scale is regressed on a set of variables nearly identical to those in the conditional WTP model. Given the categorical nature of the certainty scale, the ordered probit model is applied to two subsets of observations with "yes" and "no" responses separately. Following Loomis and Ekstrand (1998), a variable measuring the square of proposed tax payment is added to the variable set from the WTP model to capture the nonlinear effect of certainty on cost.

4.5 Variables

The dependent variables have been described with the econometric model in Section 4.2. There are seven categories of independent variables corresponding to the conceptual model: 1) quantitative environmental improvements in eutrophic lakes and greenhouse gas emission; 2) cost of hypothetical programs; 3) questionnaire version for type of land management to generate the ES (farming practice or general land management); 4) resident's perception of and attitudes about eutrophic lakes and global warming; 5) resident's opinion on general environmental issues; 6) demographic characteristics, including age, gender, education, income, household size, length of residency, whether the respondent is a farmer or forester, whether the respondent is a registered voter, and whether the respondent consider herself a Michigan resident; and 7) frequencies of fishing, swimming, boating and hiking in Michigan. The variable definitions and summary statistics can be found in Tables 4 and 5.

5 Results

The certainty-adjusted models are found to differ from the conventional dichotomous choice model in several aspects, including the significant variables, the magnitude of marginal effects, as well as the value and efficiency of welfare estimation.

5.1 Preference certainty mode

The results from two ordered probit models on determinants of certainty following “yes” and “no” responses are shown in Table 7. The two models share a common set of influential demographic characteristics, such as age, whether the respondent is a Michigan resident, and whether she belongs to environmental organizations. The certainty following “yes” responses increases with the proposed reduction in GHG for those who are very concern about global warming. The respondents are more certain about “yes” responses if they are registered voters, or go hiking near inland lakes more frequently. The certainty following “no” responses increases if the respondents have been living in Michigan for longer years, work in the forest, or go swimming and fishing in inland lakes more frequently. Depending on a “yes” versus a “no,” certainty of response is influence in opposite (but economically logical) ways by the hypothetical tax payment. For “yes” responses, decision certainty declines with increasing cost, whereas for “no” responses it rises with cost. The quadratic forms of cost are not significant in either “yes” or “no” response models, suggesting a linear relationship between cost and certainty. These results are similar to previous studies which found the bid level, prior knowledge (Loomis and Ekstrand, 1998), and respondents' attitudes towards the hypothetical market (Champ and Bishop, 2001, Samnaliev, et al., 2006) to be influential.

5.2 Conditional willingness to pay

Comparing the regression results between the conventional random effect probit model and other certainty-adjusted models (Table 8), more variables are found to be significant when incorporating decision certainty. The conventional random effect probit model suggests that the probability of voting “yes” to the proposed tax program depends on the reduction in eutrophic lakes, concern about global warming, proposed tax payment, income, age, education, and whether the respondent is a registered voter. The certainty-adjusted voting probabilities depends on these same factors, as well as the frequencies of boating and hiking, whether the respondent is involved in environmental organizations, and whether they consider themselves as Michigan residents. The constant term also becomes significant in all certainty-adjusted models. However, the variable representing the interaction between GHG reduction and whether respondents are concerned about global warming is only significant at 54-82% probability levels in certainty-adjusted models, while it is significant at the 90% level in the conventional model.

Compared with the conventional model, the marginal effects of significant variables in certainty-adjusted models are generally smaller, except for the model with fixed cutoff point (Table 9). As the variations of dependent variables are smaller in the Symmetric Uncertainty Model, the Asymmetric Uncertainty Model and the Indifferent ordered probit model, it is not surprising that the probabilities of voting “yes” are less sensitive to those significant variables.

5.3 Spike model

The spike model that estimates the influence of various attributes on the probability of having a positive WTP is a prior estimation to the conditional willingness to pay. With all the methods for adjusting preference certainty in WTP, the spike model is used to calculate the unconditional WTP. Results from the spike probability model (Table 6) suggest that the probability that a respondent had a positive WTP depends endogenously on the level of environmental improvement in eutrophic lakes and greenhouse gas, as well as the resident's concern about global warming, and demographic traits such as income, whether respondents are Michigan residents and how long they have been living in Michigan.

5.4 Welfare effect

Both the conditional and the unconditional median WTP for 140 fewer eutrophic lakes and a GHG emission reduction of 0.4% from the Year 2000 level were calculated for each respondent following both the conventional CV method and the different certainty-adjusted methods. The average median WTP across residents and a bootstrapped 95% confidence interval are shown in Table 10. The median WTP from the conventional method is the highest among all methods--$134 tax payment per year conditional on having a positive WTP and $118 unconditional WTP. The SUM method reduces the conditional and unconditional WTP to $76 and $67 respectively, while the ASUM method further lowers them to $34 and $30. The polychotomous response (Indifferent model) and dichotomous response (Fixed Cutoff model) methods with cutoff point 7 generate relatively higher WTP than the SUM and ASUM methods.

Comparing the efficiency of estimation among five models, the conventional model which does not incorporate the preference uncertainty is clearly least efficient with a high variability measure of 14.9 (Table 10). The indifference ordered probit model and the fixed cutoff model are more efficient than the conventional model, while the SUM and ASUM certainty-adjusted models result in the highest efficiency levels.

6 Conclusion

Over half of the respondents to this CV survey displayed uncertainty about their willingness to pay for a public program to reduce numbers of eutrophic lakes and to mitigate greenhouse gas emissions (Figure 5). The incorporation of preference uncertainty into binary choice models reduced median willingness to pay estimates for this public program by half or more. The certainty-adjusted models also reveal more underlying determinants of WTP that are related to the demographics and recreation experience of respondents. Comparing the four certainty-adjusted methods, the symmetric uncertainty model, which recodes the binary response to a fine grid of probability using the self-reported certainty following both "yes" and "no" responses, has the median WTP estimate with the greatest efficiency among symmetric models. In sum, incorporating self-reported certainty in the willingness to pay estimation appears to improve our understanding of the demand for ecosystem services, thereby potentially improving the design of incentive payments in PES programs.

Figures and Tables

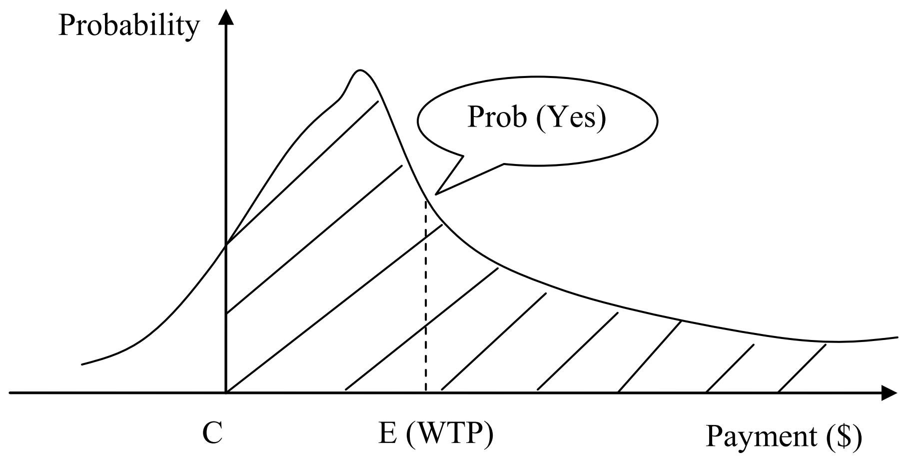

Figure 1 Probability of voting "yes" as a representation of underlying WTP with preference uncertainty

On a scale of 1 to 10, where 1 means "very uncertain" and 10 means "very certain", how certain are you with your answer in Question 15?

1	2	3	4	5	6	7	8	9	10
Very uncertain									Very certain

Figure 2 Numerical certainty scale used in survey, 2211 Michigan residents, 2009

0	.1	.2	.3	.4	.5	.6	.7	.8	.9	1.0

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increasing uncertainty of No response   increasing uncertainty of Yes response

Figure 3 Numerical certainty scale used in Loomis and Ekstrand (1998)

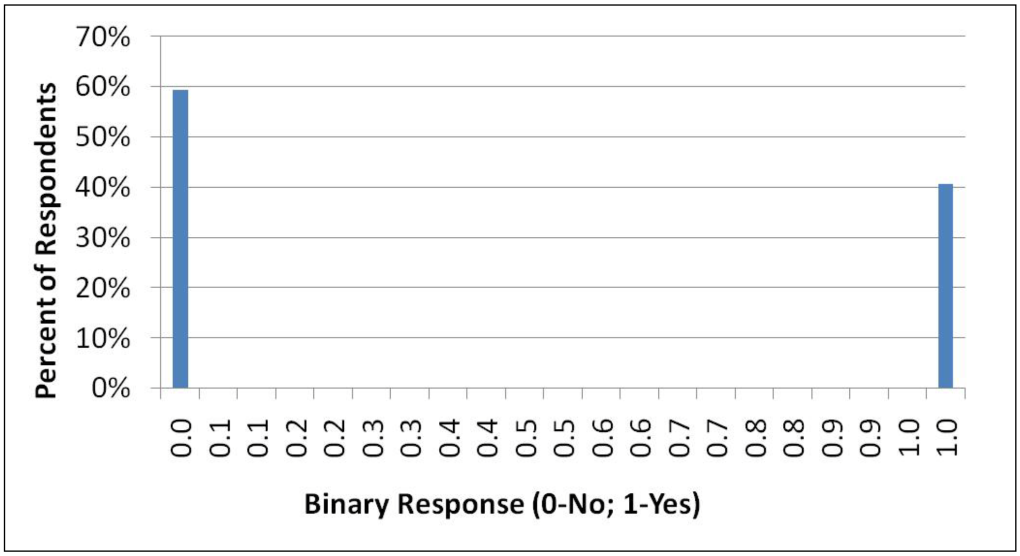

Figure 4 Binary response percentage in sample, 2211 Michigan residents, 2009

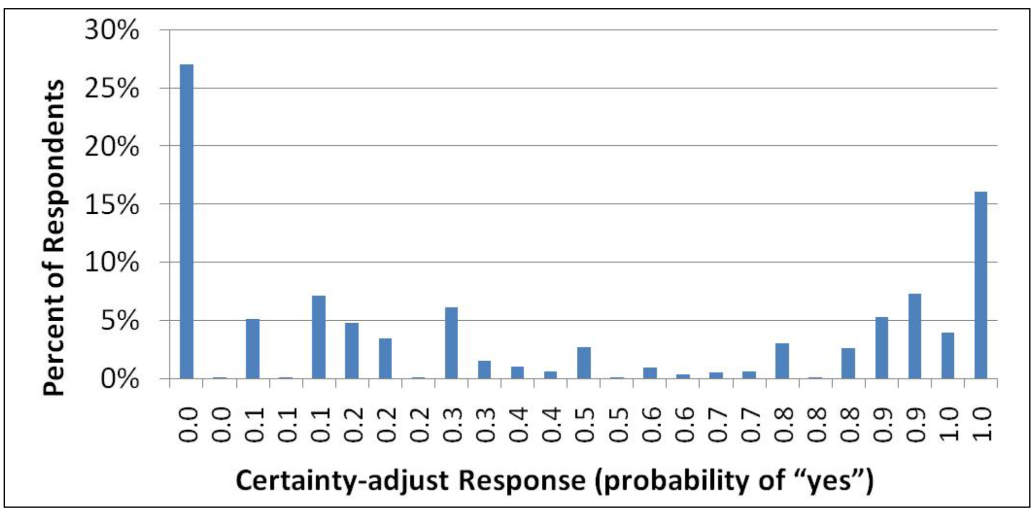

Figure 5 Certainty-adjusted response percentage under the Symmetric Uncertainty Model (SUM) in sample, 2211 Michigan residents, 2009

Table 1: Dependent variable for probit model with different cutoff certainty levels

Cutoff level	10		9		8		7	
Certainty scale	1--9	10	1--8	9--10	1--7	8--10	1--6	7--10
Y_i if answer Yes	0	1	0	1	0	1	0	1
Y_i if answer No	0		0		0		0	

Table 2: Dependent variables for ordered probit model

Certainty scale	1	2	3	4	5	6	7	8	9	10
Y_i if answer Yes	0.5						1			
Y_i if answer No							0			

Table 3: Dependent variables for fractional response models

SUM

Certainty scale	1	2	3	4	5	6	7	8	9	10
$\Pr(Y_i=1\|_{WTP>0})$ if answer Yes	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1
$\Pr(Y_i=1\|_{WTP>0})$ if answer No	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.10	0.05	0

ASUM

Certainty scale	1	2	3	4	5	6	7	8	9	10
$\Pr(Y_i=1\|_{WTP>0})$ if answer Yes	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1
$\Pr(Y_i=1\|_{WTP>0})$ if answer No	0									

Table 4: Variable description and summary statistics, 2211 Michigan residents, 2009

Variable name	Definition	Unit of measure	Ranges and levels
Contingent voting			
Vote yes	Vote on program A/B/C with proposed tax payment	binary	1-yes, 0-no
Certainty	How certain with vote on program A/B/C	category	1-very uncertain, …, 10-very certain
No-cost vote	Vote on program if it did not cost anything	binary	1-yes, 0-no
Ecosystem service change			
Lake	Eutrophic lakes that would be reduced if the program were to be implemented	number	0, 70, 140, 200, 400
GHG	Greenhouse gas reduction of the 2000 emission level that would be achieved if the program were to be implemented	%	0, 0.2, 0.4, 0.6, 1.2
Cost			
Cost	The amount of annual tax increase that would be used to fund the program	USD/year	10, 30, 50, 100, 200
Version			
Farm version	Whether the questionnaire version is the agricultural-farmer version or the general land management version	NA	0-Land management version, 1-Agricultural-farmer version
Perception and attitudes			
GW concern	Whether the respondent is concerned about global warming (GW)	category	0-Not concerned or somewhat concerned, 1-Very concerned
Demographics			
MI years	Length of continuing to live in MI	category	1-less than 1 year, 2- 1-5 years, 3- 5-10 years
MI resident	Michigan resident	binary	1-yes, 0-no
Male	Male gender	binary	1-yes, 0-no
Household num	Number of people in the household	number	
Age	Age	year	
Farmer	Whether work on a farm	binary	1-yes, 0-no
Forester	Whether work in forests	binary	1-yes, 0-no
Env org	Belong to environmental organizations	binary	1-yes, 0-no
Income	Household annual pretax income	1000 USD	
Education	Education level	category	1-Some high school or less, 2-High school diploma, 3-Technical training beyond high school, 4-Some college, 5-College degree,

			6-Some graduate work, 7-Graduate degree
Voter	Registered voter	binary	1-yes, 0-no
Recreational experiences			
Fishing freq	How often go fishing	category	1-Never, 2-In some years, 3-In most years, 4-Every year
Swimming freq	How often go swimming	category	1-Never, 2-In some years, 3-In most years, 4-Every year
Boating freq	How often go boating	category	1-Never, 2-In some years, 3-In most years, 4-Every year
Hiking freq	How often hike	category	1-Never, 2-In some years, 3-In most years, 4-Every year

Table 5: Descriptive statistics of variables

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
Contingent voting						
Vote yes	Vote on program A/B/C	3396	0.631	0.48	0	1
Certainty	How certain with vote on program A/B/C	3396	7.889	2.25	1	10
No-cost vote	Vote on program if it did not cost anything	4125	0.832	0.37	0	1
Cost	The amount of annual tax increase that would be used to fund the program	4125	64.47	62.8	10	200
Ecosystem service change						
Lake	Eutrophic lakes that would be reduced if the program were to be implemented	4125	168.8	111	0	400
GHG	Greenhouse gas reduction of the 2000 emission level that would be achieved if the program were to be implemented	4125	0.527	0.32	0	1.2
Version						
Farm version	Whether the questionnaire version is the agricultural-farmer version or the general land management version	1429	0.482	0.5	0	1
Perception and attitudes						
GW concern	Whether the respondent is very concerned about global warming (GW)	1429	0.394	0.49	0	1
GW*GHG	The interaction of GW concern and GHG reduction level	4125	0.208	0.33	0	1.2
Demographics						
MI years	Length of continuing to live in MI	1429	3.661	0.69	1	4
MI resident	Michigan resident	1429	0.99	0.1	0	1
Male	Male gender	1429	0.659	0.47	0	1
Household num	Number of people in the household	1429	2.54	1.37	0	9
Age	Age	1429	54.95	15.3	13	96.5
Farmer	Whether work on a farm	1429	0.04	0.2	0	1
Forester	Whether work in forests	1429	0.017	0.13	0	1
Env org	Belong to environmental organizations	1429	0.078	0.27	0	1
Income	Household annual pretax income (1000$)	1429	68.28	50.5	5	250
Education	Education level	1429	4.253	1.74	1	7
Voter	Registered voter	1429	0.947	0.22	0	1
Recreational experiences						
Fishing freq	How often go fishing	1429	2.195	1.17	1	4
Swimming freq	How often go swimming	1429	2.369	1.14	1	4
Boating freq	How often go boating	1429	2.43	1.11	1	4
Hiking freq	How often hike	1429	2.245	1.15	1	4

Table 6: Spike probability model, 1429 Michigan residents, 2009

	Regression coefficient			Marginal Effect		
Variable	Coef.		P>z	Coef.		P>z
Version						
Farm version	-0.051		0.760	-0.002		0.713
ES change and concern						
Lake	0.004	***	0.000	0.000	***	0.000
GHG	0.383	**	0.032	0.015	**	0.021
GW concern	1.271	***	0.000	0.019	***	0.000
Demographics						
MI years	-0.204		0.107	-0.008	*	0.067
MI resident	0.907		0.267	0.018	***	0.002
Male	-0.085		0.648	-0.004		0.595
Household num	-0.014		0.835	-0.001		0.793
Age	0.003		0.677	0.000		0.602
Farmer	-0.563		0.195	-0.036		0.263
Forester	-0.041		0.951	-0.002		0.940
Env org	-0.146		0.648	-0.007		0.609
Income	0.004	**	0.032	0.000	**	0.017
Education	0.005		0.933	0.000		0.915
Voter	0.339		0.351	0.010		0.124
Recreational experiences						
Fishing freq	-0.100		0.305	-0.004		0.217
Swimming freq	-0.003		0.976	0.000		0.970
Boating freq	-0.022		0.853	-0.001		0.815
Hiking freq	-0.100		0.277	-0.004		0.191
Constant	1.030		0.338			
/lnsig2u	1.77					
sigma_u	2.43					
rho	0.85					
Number of obs	4125					
Number of group	1429					
Wald chi2(22)	104.58					
Prob > chi2	0					
Log likelihood	-1350					

Table 7: Determinants of preference certainty for yes/no responses, 2211 Michigan residents, 2009 (Dependent variable: certainty scale [1-very uncertain; 10- very certain])

Certainty	Ordered probit for *Yes* responses Coef.		P>t	Ordered probit for *No* responses Coef.		P>t
Cost						
Cost	-0.004	**	0.030	0.003		0.114
Cost square	9.03E-06		0.230	-1.36E-05		0.158
Ecosystem service change						
Lake	0.000		0.162	0.000		0.245
GHG	-0.029		0.759	-0.065		0.565
Version						
Farm version	-0.061		0.198	0.030		0.623
Perception and attitudes						
GW concern	0.166		0.252	-0.068		0.722
GW*GHG	0.364	***	0.000	-0.037		0.760
Demographics						
MI years	-0.024		0.471	0.097	**	0.021
MI resident	0.817	**	0.050	-0.967	***	0.001
Male	0.086		0.124	0.006		0.931
Household num	0.013		0.503	-0.012		0.595
Age	0.005	***	0.005	-0.004	*	0.072
Farmer	-0.122		0.306	0.004		0.985
Forester	0.320		0.145	0.625	**	0.020
Env org	0.351	***	0.000	-0.217	**	0.039
Income	0.001		0.257	0.000		0.969
Education	-0.022		0.175	-0.005		0.807
Voter	0.194	*	0.081	-0.094		0.401
Recreational experiences						
Fishing freq	0.028		0.334	0.071	**	0.050
Swimming freq	0.012		0.724	0.082	**	0.030
Boating freq	-0.010		0.769	-0.126	***	0.001
Hiking freq	0.077	***	0.004	0.006		0.846
Number of obs	2143			1253		
Wald chi2(48)	173.07			52.1		
Prob > chi2	0			0.0003		
Pseudo R2	0.0237			0.0091		
Log pseudo likelihood	-3719.1			-2389.4		

Table 8: Comparison of regression results on probability of payment with and without certainty, 1293 Michigan residents, 2009

	Basic model		SUM		ASUM		Indifferent		Cutoff=7	
Model	RE probit		GEE fractional probit		GEE fractional probit		Ordered probit robust error		RE probit	
variable	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Version										
Farm version	-0.064	0.790	-0.024	0.654	-0.023	0.698	-0.048	0.241	-0.263	0.291
Cost										
Ln(cost)	-1.446 ***	0.000	-0.289 ***	0.000	-0.321 ***	0.000	-0.311 ***	0.000	-1.202 ***	0.000
ES change and concern										
Lake	0.004 ***	0.000	0.001 ***	0.000	0.001 ***	0.000	0.001 ***	0.000	0.004 ***	0.000
GHG	-0.220	0.403	-0.015	0.778	-0.043	0.495	0.029	0.723	-0.013	0.961
GW*GHG	0.628 *	0.078	0.111	0.180	0.135	0.139	0.118	0.385	0.246	0.466
GW	1.503 ***	0.000	0.369 ***	0.000	0.401 ***	0.000	0.397 ***	0.000	2.018 ***	0.000
Demographics										
MI years	-0.089	0.623	-0.032	0.434	-0.019	0.679	-0.042	0.169	-0.086	0.643
MI resident	1.672	0.193	0.591 **	0.016	0.531 **	0.044	0.651 ***	0.001	3.231 ***	0.007
Male	-0.190	0.494	-0.034	0.569	-0.033	0.628	-0.002	0.964	0.291	0.295
Household num	-0.024	0.817	-0.003	0.891	-0.003	0.899	0.013	0.468	0.077	0.472
Age	0.030 ***	0.002	0.007 ***	0.001	0.007 ***	0.003	0.009 ***	0.000	0.034 ***	0.000
Farmer	-0.657	0.317	-0.135	0.315	-0.162	0.294	-0.122	0.279	-0.614	0.346
Forester	0.788	0.403	0.167	0.523	0.233	0.410	-0.069	0.712	0.529	0.550
Env org	0.529	0.243	0.184 *	0.081	0.181	0.117	0.255 ***	0.004	1.125 **	0.014
Income	0.015 ***	0.000	0.003 ***	0.000	0.003 ***	0.000	0.003 ***	0.000	0.011 ***	0.000
Education	0.185 **	0.023	0.030	0.103	0.037 *	0.073	0.045 ***	0.001	0.192 **	0.023
Voter	1.770 ***	0.002	0.372 ***	0.005	0.414 ***	0.007	0.391 ***	0.000	1.572 ***	0.005
Recreational experiences										
Fishing freq	0.207	0.143	0.025	0.442	0.037	0.295	0.026	0.294	0.125	0.387
Swimming freq	0.089	0.581	0.013	0.712	0.026	0.515	0.002	0.930	0.170	0.295
Boating freq	0.141	0.405	0.051	0.178	0.039	0.365	0.058 **	0.036	0.147	0.395
Hiking freq	0.150	0.274	0.042	0.161	0.050	0.130	0.051 **	0.027	0.259 *	0.062
Constant (cut 1)	-2.048	0.218	-0.717 **	0.040	-0.885 **	0.022	0.538		-6.795 ***	0.000
Cut point 2							1.275			
/lnsig2u	2.60								2.61	
sigma_u	3.66								3.68	
Rho	0.93								0.93	
Number of obs	3396		3396		3396		3396		3396	
Number of group	1293		1293		1293				1293	
Wald chi2(22)	234.05		299.45		274.48		530.45		272.95	
Prob > chi2	0		0		0		0		0	
Log likelihood	-1367						-3239		-1461	

Table 9: Comparison of regression results on probability of payment with and without certainty, 1293 Michigan residents, 2009

	Basic model		SUM		ASUM		Indifference		Cutoff7	
Model	RE probit		GEE fractional probit		GEE fractional probit		Ordered probit robust error		RE probit	
variable	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Version										
Farm version	-0.009	0.740	-0.008	0.573	-0.008	0.626	-0.017	0.139	-0.045	0.180
Cost										
Ln(cost)	-0.211 ***	0.000	-0.102 ***	0.000	-0.114 ***	0.000	-0.111 ***	0.000	-0.204 ***	0.000
ES change and concern										
Lake	0.001 ***	0.000	0.000 ***	0.000	0.000 ***	0.000	0.000 ***	0.000	0.001 ***	0.000
GHG	-0.032	0.291	-0.005	0.722	-0.015	0.390	0.011	0.655	-0.002	0.951
GW*GHG	0.092 **	0.025	0.039 *	0.091	0.048 *	0.062	0.042	0.274	0.042	0.359
GW	0.175 ***	0.000	0.122 ***	0.000	0.135 ***	0.000	0.140 ***	0.000	0.319 ***	0.000
Demographics										
MI years	-0.013	0.535	-0.011	0.323	-0.007	0.602	-0.015 *	0.082	-0.015	0.559
MI resident	0.188 **	0.016	0.185 ***	0.000	0.175 ***	0.005	0.223 ***	0.000	0.441 ***	0.000
Male	-0.028	0.398	-0.012	0.474	-0.012	0.542	-0.001	0.954	0.050	0.188
Household num	-0.003	0.771	-0.001	0.862	-0.001	0.873	0.005	0.360	0.013	0.364
Age	0.004 ***	0.000	0.002 ***	0.000	0.002 ***	0.000	0.003 ***	0.000	0.006 ***	0.000
Farmer	-0.102	0.224	-0.048	0.210	-0.058	0.187	-0.044	0.169	-0.102	0.220
Forester	0.104	0.229	0.057	0.408	0.080	0.284	-0.025	0.641	0.090	0.449
Env org	0.072	0.114	0.063 **	0.023	0.063 **	0.044	0.091 ***	0.000	0.189 ***	0.001
Income	0.002 ***	0.000	0.001 ***	0.000	0.001 ***	0.000	0.001 ***	0.000	0.002 ***	0.000
Education	0.027 ***	0.004	0.011 **	0.040	0.013 **	0.024	0.016 ***	0.000	0.033 ***	0.004
Voter	0.196 ***	0.000	0.123 ***	0.000	0.140 ***	0.000	0.138 ***	0.000	0.257 ***	0.000
Recreational experiences										
Fishing freq	0.030 *	0.064	0.009	0.332	0.013	0.186	0.009	0.185	0.021	0.275
Swimming freq	0.013	0.487	0.005	0.642	0.009	0.412	0.001	0.912	0.029	0.186
Boating freq	0.021	0.291	0.018 *	0.089	0.014	0.253	0.021 ***	0.008	0.025	0.284
Hiking freq	0.022	0.167	0.015 *	0.077	0.018 *	0.056	0.018 ***	0.005	0.044 **	0.017

Table 10: Comparison of median WTP (in U.S. dollars) and estimation efficiency

	Basic model	SUM	ASUM	Indifference	Cutoff=7
	RE probit	GEE fractional probit	GEE fractional probit	Ordered probit	RE probit
Conditional WTP					
Median WTP	134	76.1	34.4	97.8	40.1
95% lower CI	-867	16.4	16.5	-28.8	0.8
95% upper CI	1135	136	52.3	225	79.5
efficiency	14.9	1.57	1.04	2.59	1.96
Mean spike probability	0.876	0.876	0.876	0.876	0.876
Unconditional WTP					
Median WTP	118	66.7	30.1	85.7	35.2
95% lower CI	-760	14.3	14.4	-25.3	0.684
95% upper CI	995	119	45.9	197	69.7
efficiency	14.9	1.57	1.04	2.59	1.96

*Notes:

- Median WTP is calculated instead of mean due to the fat tail in the exponential functional form of WTP .
- Only variables that are significant at 90% level are included in the WTP calculation.
- 95% confidence interval is obtained by bootstrapping with 200 replications.
- Efficiency is calculated as $(CI_{upper} – CI_{lower})$ / Median (WTP). A lower value indicates higher efficiency.
- The 18.6% protest rate of nonresponse is not factored into the results

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