ESSAYS ON RECREATION DEMAND AND STRUCTURAL MODEL OF USE AND NON-USE VALUES OF WATER QUALITY IMPROVEMENT

By

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ABSTRACT

This dissertation consists of three essays addressing non-market valuation of changes in environmental quality. The first two essays develop and test structural models of use and non-use demand for ecosystem services and the last essay focuses on applications of the methods in empirical settings. This dissertation aims to provide theory-based empirical methods to elicit individual's willingness to pay for environmental quality improvement in the context of water resources.

ESSAY 1: Estimating Recreation Demand with Incomplete Trip Location Information

The first essay derives valid estimation procedures in recreation demand models with incomplete data on trip locations. Recreation datasets will often lack details on the locations of some or most trips, and it raises concern that standard estimators could yield biased results. To address this, I derive a likelihood function that is appropriate with or without complete information on trip locations. Using Monte Carlo simulation, I compare three nested logit estimators. In an empirical application, I use data from a web-based survey of trips in Michigan during the summer 2018 to estimate a recreation demand model. Monte Carlo results and empirical results show that a convenient trip-weighting strategy that can be implemented in existing nested logit software closely approximates true values and values from a more complex structural model that fully accounts for the censored data.

ESSAY 2: Testing the Robustness of a Structural Model for Discerning Use and Non-use Values of Ecosystem Services

A theoretically consistent structural model facilitates definition and measurement of use and non-use benefits of ecosystem services. Unlike many previous approaches that utilize multiple stated choice situations, we apply this conceptual framework to a travel cost random utility model and a consequential single-referendum contingent valuation research design for simultaneously estimating use and non-use willingness to pay for environmental quality improvement. We employ Monte Carlo generated data to evaluate properties of key parameters and examine the robustness of this method of measuring use and non-use values associated with quality change. The simulation study confirms that this new method can

generally, but not always, be applied to successfully identify use and non-use values of various ecosystems while consistency is ensured.

ESSAY 3: Comparing Structural Estimation of Use and Non-use Values for Water Quality to Simpler Ad hoc Approaches

The third essay assesses two components of welfare gains from water quality improvements using a structural model of use and non-use values. The combined revealed and stated preference model, based on a random utility travel cost model (RP) and contingent valuation (SP) method, measures both use and non-use values for water resources. I use recreation use and survey referendum data of the Michigan general population, consistently collected in a web-based survey. First, I estimate use values from a recreation demand model based on travel cost and trip-level data that each respondent reported. Then, I use the stated preference data to estimate total values of water quality improvement for changes in statewide water quality. Third, I extend the structural model of Day et al. (2019) to separately identify use and non-use values via joint estimation and validate the methodology. This paper builds on and contributes to literature on methodologies for estimation and delineation of use and non-use values.

I dedicate this dissertation to my family. I owe everything to you.

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Writing this dissertation has been the longest project that I ever carried out in my life. It was the reason I was sitting at my office desk all day and night long. It is the product of my past five years and inputs such as youth and health. The significant amount of time and energy (`blood, sweat, and tears') put into this dissertation. Looking back, I am grateful for the truth and contentment that I discovered during the process. I send the deepest appreciation to everyone who made it possible.

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I once had a belief that this dissertation would serve as a monument to my scholarly knowledge. Feeling the pressure, I challenged myself to create something worth. I sought out an engaging topic that would be worth the time and effort for both writers and readers, a research agenda of significant scholarly value that had yet to be fully explored, or a policy question that demanded attention. Despite my efforts to come up with such a research idea, I found myself increasingly distant from completing my dissertation. I redirect my focus from those unattainably high standards to crafting a paper with sound hypothesis, sufficient power, and a clear response to primary research questions. Now I am embracing this far-from perfect manuscript with all its limitations, as a beginning of my academic journey and a summary of the executed research during the doctoral program. I hope readers of this dissertation will find a small piece of usefulness in it. My only ambition is to continue conducting research and writing papers for the rest of my life.

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Essay 1: Estimating Recreation Demand with Incomplete Trip Location Information

1.1. Introduction

Water resources provide valuable recreation services such as fishing, swimming, wading, floating, boating, and walking on the shore. The demand (i.e., participation and site selection) for water-based recreation activities may depend on the characteristics and ecosystem services of the waterbodies. However, there is no directly observable price measure for the marginal value of quality change in ecosystem services. The most common valuation approach in recreation demand literature is a travel cost model (Habb & McConnel, 2002; Parsons, 2017). To measure the value of sites and valuing changes in the quality of ecosystem services, various multi-site demand models are utilized. These approaches typically consider the full price of a visit to a site, a set of substitute prices for visits to other sites, and site attributes to specify a demand system for visits to the relevant set of recreation sites.[1] Since these demand systems are based upon actual choices that individuals make across the set of sites, they are data intensive (Lupi, Phaneuf, & von Haefen, 2020).

Despite a volume of literature linking recreation demand to changes in water quality, an empirical gap persists due in part to data availability on the number of trips to individual sites. Due to lack of administrative or other trip data, empirical analysis relies on self-reported trip counts and locations collected through surveys (Lupi, Phaneuf, & von Haefen, 2020). Some recreation surveys typically are designed to permit respondents to report counts of the number of trips to a set of sites over a certain period. However, in general, it is hard to get a complete inventory of such trips. In many cases, a researcher only observes aggregate data on the total number of trips and trip details for one or a small subset of recreation sites, rather than detailed trip information for each site in a choice set.

To tackle these data collection challenges, researchers design a survey with a pre-established list of sites. The 2002-2005 Iowa Lakes surveys used in Yi & Herriges (2017) and Jeon & Herriges (2010) provide survey respondents with a complete list of 131 lakes in Iowa and have them report the frequency of their

[1] See the chapter 9 in Freeman III et al. (2014) and the chapter 17 of Phaneuf & Requate (2016) for an overview of the literature in this field.

visits to each lake, which is feasible when there are not a large number of possible sites. Similarly, the Alberta Moose Hunting Study data sets used by Adamowicz et al. (1997), von Haefen & Phaneuf (2008), and Jeon & Herriges (2017) include a list for descriptions of 10 recent moose hunting trips (Mcleod et al., 1993). The canonical repeated random utility paper by Morey et al. (1993) models anglers' participation and site choice decisions using the full information on the number of trips to eight distinct Atlantic salmon fishing areas. However, such data could be imperfect because of recall bias and inattention bias when the number of alternatives is large. Yet, in many relevant recreation choice situations, the number of feasible substitutes is too large to be listed *a priori* in a survey (Freeman III et al., 2014; Phaneuf & Requate, 2016).

Another approach in data collection is to gather detailed information on only a subset of the trips taken by an individual (Parsons, 2017; Lupi, Phaneuf, & von Haefen, 2020). Specifically, a researcher can focus on a single quasi-random site visited by a respondent and weigh the choices made on that trip to reflect the total number of trips taken during a season (Freeman III et al., 2014). The use of such "representative" trips trades off loss of trip details for lower recall bias associated with gathering a complete inventory of trips. The literature contains many variations of this strategy. For example, a study of the Deepwater Horizon oil spill by English et al. (2018) takes a similar approach to gather a panel of recreational trip data. They focus on details of up to three of the most recent trips, and for other sites, they only collect destinations and counts. A related strategy was used in an assessment of recreational losses associated with the Cosco Buson oil spill (English, 2010). Similarly, Dundas & von Haefen (2020) estimate fishing site choices using a data set on locations of a single trip and then combined the resulting site choice model with data on total trips from a separate survey that lacked trip locations. An approach that is related to trip-weighting during estimation is to estimate site choice models using the information on a single trip location, and then scale the model results to a population level by multiplying by total trips ex-post rather than during model estimation (Alvarez et al., 2019; Alvarez et al., 2014; Knoche & Lupi, 2007). Lupi & Feather (1998) scale last trip data in a site choice model by the number of trips and use this in estimation, and Feather & Hellerstein (1997) develop a site choice model that scales choices from up to three sites by their trips and then uses the estimates in a second stage estimation of total trips. Finally, Haab et al. (2008) estimate their model based on the last trip taken by the angler, which was part of a data set with incomplete trip information collected in Hawaii.

This paper contributes to the literature by examining whether incomplete information on all trip locations adversely affects estimation results and by addressing possible methods to avoid misidentification due to limited information on individual choice sets and site characteristics. Using a Monte Carlo simulation, I generate pseudo data sets and use them to run three nested logit models. The first model uses the full inventory of the number of trips taken to each site, which is only possible when one has complete trip information. The second and third models are both based on incomplete trip location data, which focus on information on one randomly selected site along with the total number of trips. The second model (called *weighting method*) weights the likelihood function for identified trips to the single site by the total number of trips people take, as is done in some of the literature, which effectively treats all trips as if they are from the one observed location. The third model (called *structural methods*) corrects the likelihood function for the unobserved trip locations to estimate revealed preference models under incomplete information. The Monte Carlo reveals that the results are consistent for all three models regardless of full information availability. Parameter estimates from the three models are similar when the number of site choices is small, but the third model most accurately estimates true values of parameters when there are a larger number of site alternatives.

In an empirical example that builds on the Monte Carlo findings, I estimate multi-site recreation demand models of two different likelihood functions with incomplete trip information. I test this because results using real data can differ from ones produced in a controlled experimental setting. Our empirical approach combines survey data and travel costs derived from an online survey for Michigan residents water-based recreation trips during Summer 2018.

With these data, I estimate a nested logit model to characterize demand for water-based recreation to waterbodies in Michigan under the framework of the repeated random utility model (McFadden, 1974; Morey et al., 1993). I find the price coefficient to be negative and significant; people prefer recreation sites that are less costly to visit, *ceteris paribus*. Alternative specific constants (ASCs, i.e., site fixed effects) are also estimated for all the sites in the model. These fixed effects define non-price attributes in the deterministic component of utility that individuals get from visiting each site. Using the estimated ASCs, a second stage regression identifies the effects of observed site characteristics (i.e., water quality) on recreation demand by taking the estimated site-specific constants and regressing them on-site attributes (Murdock, 2006). I utilize all sites in estimating the parameters of the site characteristics in our study area, the Lower Peninsula of Michigan. The results show a positive correlation between water quality and site-specific constants.

The remainder of this paper contains six sections. Section 2 describes the model to illustrate the observed trip patterns under the random utility framework. Section 3 presents simulation exercises using pseudo-data sets and the repeated nested logit model, and Section 4 reports the results of the simulations. Section 5 describes data and the empirical strategy for the application. Estimation results are discussed in Section 6. Section 7 concludes.

1.2. Models of Multidimensional Choices and the Nested Logit Model

Consider a single-year multiple-site model, often referred to as the repeated logit model (Morey et al., 1993). Each individual has *J+1* choice alternatives (*J* sites and the option to stay at home) and T choice occasions. In the context of recreational usage, the number of weeks during a study period is sometimes chosen as the total number of choice occasions, *T*. On each choice occasion, the number of site alternatives available is fixed, and each individual is assumed to take at most one trip. The conditional indirect utility that individual *i* receives from choosing alternative *j* on choice occasion *t* is written as

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \tag{1}$$

where V_{ijt} is a systematic component of the utility function determined by observed attributes of each alternative and ε_{ijt} is the idiosyncratic error term, representing variation in preferences due to unobserved attributes of individuals and sites that are not captured by V_{ijt}. The errors are assumed to be independent and identically distributed across individuals and choice occasions. For identification in random utility models, only relative differences in indirect utility matter.

A researcher does not observe U_{ijt} but observes choice outcomes for each individual (i.e., y_{ijt}) for all $i = \{1, \cdots, N\}$, $j = \{0, \cdots, J\}$, and $t = \{1, \cdots, T\}$.

$$y_{ijt} = \begin{cases} 1 & if\ U_{ijt} > U_{ikt}\ \forall\, k \neq j, \forall\, t \\ 0 & otherwise \end{cases} \tag{2}$$

The probability of choosing alternative 1 at each choice occasion *t* is given by

$$P_{i1t} = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} 1\big(V_{i1t} - V_{ijt} > \varepsilon_{ijt} - \varepsilon_{i1t},\ \ \forall j \neq 1\big) dF(\varepsilon_{i\cdot t}^{1}) \tag{3}$$

where $F(\boldsymbol{\varepsilon}_{i\cdot t}^{\mathbf{1}})$ denotes the joint distribution of $\boldsymbol{\varepsilon}_{i\cdot t}^{\mathbf{1}}$, a vector of idiosyncratic error terms for all the sites *j* other than $j = 1$, that is, $\boldsymbol{\varepsilon}_{i\cdot t}^{\mathbf{1}} = \big(\varepsilon_{i2t}^{1}, \cdots, \varepsilon_{iJt}^{1}\big)'$.

Complete specification of the choice model then requires specifying the structure of the V_{ijt}'s and the distribution assumptions for the ε_{ijt}'s. Following much of the recreation demand literature, the deterministic component of conditional indirect utility from visiting a site *j* is denoted in terms of two types of parameters: alternative-specific constant (ASCs) α_j's and a cost coefficient γ_c. In this case, the deterministic component of utility does not vary over time since travel cost does not vary over time, so that

$$V_{ijt} = V_{ij} = \begin{cases} 0 & if\ \mathrm{j} = 0 \\ \alpha_j + \gamma_c C_{ij} & if\ j = 1, \cdots, J \end{cases} \tag{4}$$

where the utility of the staying at home option, V_{i0}, has been normalized to zero. Alternative specific constants are fixed effects that define non-price attributes in the deterministic component of utility that individuals receive from visiting each site. The parameter α_j captures the mean of unobserved characteristics and can be thought of as measuring the overall "appeal" of a recreation site. The cost coefficient γ_c denotes the travel cost parameter. C_{ij} denotes individual *i*'s cost of visiting site *j*. The marginal effect of site attributes q_j can be identified with a two-stage estimation (Murdock, 2006).

By assumption, the distribution of $F(\cdot)$ follows a generalized extreme value (GEV) distribution, yielding the nested logit model (Train, 2009). In this specification, the error terms ($\varepsilon_{ijt}{}'s$) for $j = 1, \cdots, J$ are correlated with each other, but not with ε_{i0t}, suggesting that the trip alternatives are more similar to each other than to the stay-at-home option.

The choice probabilities can then be rewritten as

$$P_{ijt} = Prob\big(y_{ijt} = 1\big) = Prob\big(y_{ijt} = 1\big|y_{i0t} = 0\big)\, Prob(y_{i0t} = 0) = P_{ij|Trip}P_{Trip} \tag{5}$$

where the probability of visiting site *j* conditional on choosing to take a trip is given as

$$P_{ij|Trip} = \frac{exp\,(\frac{V_{ij}}{\theta})}{\sum_{r=1}^{J} exp\,(\frac{V_{ir}}{\theta})} \tag{6}$$

and the probability of taking a trip becomes

$$P_{Trip} = \frac{\left[\sum_{r=1}^{J} exp\left(\frac{V_{ir}}{\theta}\right)\right]^{\theta}}{exp\,(V_{i0}) + \left[\sum_{r=1}^{J} exp\left(\frac{V_{ir}}{\theta}\right)\right]^{\theta}} = \frac{\left[\sum_{r=1}^{J} exp\left(\frac{V_{ir}}{\theta}\right)\right]^{\theta}}{1 + \left[\sum_{r=1}^{J} exp\left(\frac{V_{ir}}{\theta}\right)\right]^{\theta}} \tag{7}$$

Substituting the equations (6) and (7) into (5), the choice probability in the nested logit model for sites *j* = 1, ⋯, J is rewritten as

$$P_{ij} = P_{ijt} = P_{ij|Trip}P_{Trip} = \frac{exp\,(\frac{V_{ij}}{\theta})\left[\sum_{r=1}^{J} exp\left(\frac{V_{ir}}{\theta}\right)\right]^{\theta-1}}{1 + \left[\sum_{r=1}^{J} exp\left(\frac{V_{ir}}{\theta}\right)\right]^{\theta}} \tag{8}$$

The dissimilarity coefficient, $\theta \in (0,1]$, measures the correlation among the ε_{ijt}'s for the trip alternatives on a given choice occasion. When θ is close to 0, the alternatives are similar to each other. A higher value of θ means greater independence and less correlation (Train, 2009). When θ is equal to 1, the model is identical to the conditional logit model.

Given a complete inventory of an individual's choices, the log-likelihood function of individual *i* in each choice occasion is

$$\begin{gathered} L_{it}(\boldsymbol{y_i}) = \prod_{j=0}^{J} P_{ij}^{y_{ij}} \\ lnL_{it}(\boldsymbol{y_i}) = \sum_{j=0}^{J} y_{ij}lnP_{ij} \end{gathered} \tag{9}$$

As choice occasions are independent, the log-likelihood function of individual *i* can be aggregated in terms of $\boldsymbol{n_i}$. The total number of times that individual *i* chooses site *j* across T choice occasions is denoted as $\boldsymbol{n_i} =$

$(n_{i0}, \cdots, n_{iJ})$ where $n_{ij} = \sum_{t=1}^{T} y_{ijt}$. The number of total trips is equal to the number of total choice occasions (T) minus the number of times no trip is chosen (n_{i0}), so $T - n_{i0}$.

$$lnL_i = lnL_i(\boldsymbol{n_i}) = \sum_{t=0}^{T} \sum_{j=0}^{J} y_{ijt} lnP_{ijt} = \sum_{j=0}^{J} n_{ij} lnP_{ij} \tag{10}$$

The log-likelihood function with complete trip location information can be rewritten as

$$lnL_i = n_{i0} lnP_{i0} + \sum_{j=1}^{J} n_{ij} lnP_{ij} \tag{11}$$

In many survey data sets, analysts acquire information on the total number of trips that respondents took and details on one specific site, denoted by $\tilde{J}$, that they went most frequently or most recently (Freeman III et al., 2014; Parsons, 2017). The choice of the reported site is quasi-random (e.g., the last trip of the trip closed to a certain date). It is not necessarily always true that the reported site is the most frequently visited. To account for the limitation of aggregate trip location data for revealed preference analysis, I introduce two additional approaches for maximum likelihood estimation in this paper: a weighting method and a structural method. Both methods focus on a quasi-random single site, visited by a respondent among J site alternatives but differ in the likelihood functions.

The weighting model adapts a standard likelihood function in equation (11). That replaces the second term that weights the choice probability of visiting the site $\tilde{J}$ by the total number of the trips, $T - n_{i0}$.

$$lnL_i = n_{i0} lnP_{i0} + (T - n_{i0}) lnP_{i\tilde{J}} \tag{12}$$

where the first term, the probability of each individual staying at home, is identical across the three different models.

The structural model uses a censored likelihood function for structural estimation. Since each choice occasion is independent, the log-likelihood function can be written as

$$ln\widetilde{L_{iJ}} = n_{i0} lnP_{i0} + lnP_{i\tilde{J}_i} + (T - n_{i0} - 1)\ln(1 - P_{i0}) \tag{13}$$

The log-likelihood function is composed of three terms. The first term captures the probability associated with the number of times the individual chooses to stay at home (n_{i0}). The second term captures the probability associated with the known decision that they made a visit to the site $\widetilde{J_i} \in \{1, \cdots, J\}$. The final term captures the total probability that individual i went on a trip to any one of the J sites on the remaining times they took a trip. This last term captures the fact that I know they took $T - n_{i0} - 1$ additional trips, but do not know the specific destination.

1.3. Generated Data Experiments

To conduct the Monte Carlo exercise to explore the properties of the three modeling approaches, I first specify the true model

$$y_i = f(X_i, \beta; \varepsilon_i) \tag{14}$$

where a stochastic component ε_i follows the model specification.

Then, a series of R datasets of length with N observations are constructed using pseudo-random numbers ε_i^r drawn from a known distribution.

$$y_i^r = f(X_i, \beta; \varepsilon_i^r), \qquad i = 1, \cdots, N;\ r = 1, \cdots, R \tag{15}$$

Finally, I use the pseudo-data sets to test the performance of alternative estimators and measure the impact of model specification. For estimation, I apply the maximum likelihood method, which uses the equations presented above each model to calculate choice probabilities for each site. The value of choice probabilities enters the log-likelihood function, and the program produces estimates and sampling variance of true parameters (Train, 2009).

The Monte Carlo analysis enables us to generate sequences that mimic truly random numbers drawn from the distribution of interest and test estimation routines. The pseudo-data sets are constructed to resemble a simplified structure of the survey data that I will use for empirical analysis.

The specific steps used to generate a series of R data sets are as follows:

Step 1. Set values for the number of observations N, site choices J, and choice occasions T.

Step 2. Choose true values for cost parameters γ_c and the dissimilarity coefficient θ.

Step 3. Draw the vector of travel costs for each person from the following distribution:

$$C_{i0t} = 0 \tag{16}$$

$$C_{ijt} \sim 5 \cdot Unif[0,1], \qquad \forall j = 1, \cdots, J$$

Since the travel cost for individual *i* to site *j* is identical on every choice occasion, $C_{ijt} = C_{ij}$.

Step 4. Draw the alternative specific constants $(\alpha_1, \alpha_2, \cdots, \alpha_J)$ from a random distribution following

$$\alpha_j \sim Unif[-2,-1], \qquad \forall j = 1, \cdots, J \tag{17}$$

Step 5. Randomly assign the number of trips to each site following the procedure described below. First, calculate lower and upper bounds of choice probabilities for each site, based on choice probabilities calculated using the basic nested logit model. Then, for each observation, a random number representing one error term is drawn from a uniform distribution $Unif[0,1]$. If the random number for site *j* is between the lower and upper bounds of choice probabilities for site *j*, I add one trip to the number of trips (Herriges & Kling, 1997). This step allocates the number of trips taken by each individual to each alternative and allows us to generate a pseudo data set as if we have full information on a panel of trip choices.

For each generated sample, I estimate the nested logit model. In estimation, I compare three cases. First, I present the model for revealed preference data with full trip information to 64 sites (Model with full data; model 1). To represent the survey data, the following values are used: J= 64, N = 3,500 and T = 60 choice occasions. In estimation, the log-likelihood functions in equations (9)-(11) are used for model 1.

Second, I consider revealed preference data with incomplete information so that for each person, their total trips are known, but the location is only known for one randomly chosen trip. To select the trip with a known location, I start the same data generated in the first case and add a procedure to modify the data structure by selecting one trip from trips $(T - n_{i0})$ to sites 1 to through J, where T is the total number of trips and n_{i0} is the number of occasions staying at home. The probability that site *j* is selected is proportional to n_{ij}, for $j = 1, \cdots, J$. That is,

$$\Pr(\tilde{J}_i = j) = \frac{n_{ij}}{\sum_{k=1}^{J} n_{ik}} \tag{18}$$

mimicking the notion that the individual randomly chooses a single site to report on. The rationale behind it is that, on average, for a large sample, the distribution will converge to the right distribution of individuals.

In estimation with the incomplete trip location data, the log-likelihood function in equation (12) is used for the *weighting* model (model 2), and the log-likelihood function in equation (13) is used for model 3.

Estimation routines for maximizing nonlinear functions in the program GAUSS are used to obtain the maximum likelihood estimates. The performance of the model is evaluated at different sample sizes (N= 1,000, 3,500, and 10,000). To begin with a simple case of the structural framework, the models with the different number of choice alternatives (J= 5, 38, and 64) are estimated. The results are represented below.

1.4. Generated Data Experiments Results

Tables 1.1 and 1.2 present the Monte Carlo simulation results when the number of choice alternatives is five (J=5). The results in the two tables differ in the number of observations, N=1,000 and N=3,500. True values of parameters are estimated using three different versions of the nested logit model. Averages and standard deviations of the estimated coefficients are calculated from the Monte Carlo simulation with 100 iterations. The last three columns in the tables display the average differences between model estimates and true values; it means that I calculate the difference between true values and estimates at each replication and take the average values. Bootstrap standard errors are reported in parentheses. Compared to true values, all the three models consistently estimate the underlying parameters, and estimates are statistically significant at the 1% confidence level. Moreover, none of the parameter estimates is statistically different from the true parameters at any reasonable significance level.

In the Monte Carlo exercises, the pseudo-data sets are constructed as if an analyst can observe a set of the numbers of trips to all the site alternatives from n_{i0} to n_{iJ}. Full information on trip details is used to estimate the full data model (Model 1) with the likelihood function from equation (11). Then, assuming that observable data lack such rich information on the number of trips to individual sites, I use a weighting method (Model 2) and a structural model (Model 3). Models 2 and 3 estimate alternative specific constants and price parameters using incomplete data. Model 2 uses a different data set from one used in the model 1 estimation with the likelihood function from equation (12). Model 3 provides estimates for the model with the censored likelihood function in equation (13).

Table 1.1: Monte Carlo Results for Average Differences Between
Model Estimates and True Values (N = 1,000, J=5, T= 60)

	True Values	Full Data (Model 1)	Incomplete Data Weighting Model (Model 2)	Incomplete Data Structural Model (Model 3)
α_1	-1.750	0.001 (0.041)	0.007 (0.119)	0.004 (0.102)
α_2	-1.547	0.000 (0.036)	0.000 (0.094)	0.004 (0.081)
α_3	-1.216	0.000 (0.026)	0.007 (0.096)	0.002 (0.080)
α_4	-1.037	0.000 (0.023)	0.000 (0.074)	0.000 (0.059)
α_5	-1.290	0.000 (0.028)	0.004 (0.092)	0.000 (0.075)
β_c	-0.400	0.000 (0.013)	0.001 (0.014)	0.000 (0.014)
θ	0.800	0.000 (0.029)	0.001 (0.061)	0.000 (0.055)

Note: Bootstrap standard errors in Parentheses.

Table 1.2: Monte Carlo Results for Average Differences Between
Model Estimates and True Values (N = 3,500, J=5, T= 60)

	True Values	Full Data (Model 1)	Incomplete Data Weighting Model (Model 2)	Incomplete Data Structural Model (Model 3)
α_1	-1.750	0.001 (0.022)	0.006 (0.060)	0.002 (0.053)
α_2	-1.547	0.001 (0.018)	0.003 (0.056)	0.005 (0.049)
α_3	-1.216	0.001 (0.013)	0.000 (0.045)	0.000 (0.036)
α_4	-1.037	0.001 (0.012)	0.001 (0.040)	0.000 (0.033)
α_5	-1.290	0.000 (0.015)	0.001 (0.050)	0.003 (0.043)
β_c	-0.400	0.000 (0.007)	0.000 (0.007)	0.001 (0.007)
θ	0.800	0.001 (0.016)	0.001 (0.031)	0.000 (0.029)

Note: Bootstrap standard errors in parentheses.

Model 1 with full data outperforms in terms of estimation of true parameters. The average differences between model 1 estimates and true values are the smallest among the three models. The model 1 estimates are also the most accurate, with their standard errors also being the smallest. The estimates from model 2 and model 3 are similar, but the model 3 estimates are slightly better in terms of precision because the standard errors of model 3 are smaller than that of model 2.

The simulation results show that both models 2 and 3 work reasonably well, despite the lack of full trip details. The weighting method with bootstrap standard errors is almost as good as the structural method, especially with larger sample sizes. Also, with less data (N=1,000), the model 2 estimates are less precise, but models 2 and 3 have similar precision with more observations (N=3,500).

When alternating the number of site choices, J, from J=38 to J=64, the results are comparable with the previous findings (Tables A.2. to A.3.). Tables in the appendix show the simulation results using the different number of observations (N=1,000, 3,500, and 10,000).

The Monte Carlo results demonstrate that two approaches for incomplete trip information – weighting the number of the chosen site by the total number of trips taken (Model 2) or structurally estimating a censored likelihood function (Model 3) – are empirically robust to Model 1 estimation using full trip information. The model estimates show that the model using full data best describes true parameters of choice data, but the variation in models does not affect estimation results in terms of the magnitude of coefficients.

1.5. Application: Michigan Recreation Demand and Water Quality Data

Having completed the Monte Carlo pseudo data experiment, I have now moved on to analyzing real data obtained from Michigan Recreational Demand and Water Quality Valuation project. Specifically, I have applied the methods outlined above to a pilot survey, which was administered online to Michigan residents in Fall 2018. This is the same survey of which stated preference data was used in Lupi et al. (2023). The Michigan Recreational Demand and Water Quality Valuation project is an integrated valuation modeling study that uses survey methods to assess changes in freshwater ecosystem services within the state.

As part of the survey, respondents were asked to report their visitation patterns to the primary recreational site of Michigan waterbodies in the reference preference section. The study concentrated on recreational trips to waterbodies that occurred between June and August of 2018. To obtain a random sample of Michigan residents, a professional market research agency (Qualtrics) was subcontracted to recruit participants. Respondents who were below 18 years old were excluded a priori. A total of 3,770 individuals completed the survey online.

Individuals were asked about the number of water-based recreation trips they took from June 1, 2018, to August 31, 2018, for the primary purpose of water-based recreation. Throughout the paper, I use the term "Summer 2018" and refer to this period. 86% of the 3,770 respondents answered that they went to any Michigan river, lake, or Great Lakes at least once in the last two years (2016-2018). 71% of them reported that they went to any Michigan waterbodies in Summer 2018. Conditional on taking a trip, they took an average of ten trips to Michigan waterbodies in Summer 2018. 30% of respondents reported that they went on both multiple and single-day trips. 35% of them responded that they took single day trips but not multiple day trips. 6% of them took multiple day trips but not single-day trips. 29% of respondents did not take any trip. 1,086 respondents stayed at home on all the choice occasions.

For those who had taken at least one trip in the summer of 2018, respondents were also asked to provide specific details of one random trip they took. An algorithm was programmed into the survey so that for people with more than one trip, either the first or last trip was randomly chosen from their single day or multiple day trips. Then, they were instructed to click the location of the trip using a Google map tool embedded in the survey and name the waterbody and the nearest city to it. Of the total respondents, 2,599 respondents identify their trip location using the map tool. 62% of the 2,599 respondents reported that they are highly confident about the location they selected on the map. 30% of them said that they are somewhat confident. 6% reported that they are not very confident, and 2% are not at all confident. In the current version of this paper, I focus on the respondents that were either very or somewhat confident about the precision of geographic information data about their trip.

The sites are defined based on watershed units delimited by United States Geological Survey (USGS) and denoted as Hydrological Unit Codes (HUCs). Figure 1.1 illustrates the HUC watersheds used as the sites in the demand model, which are defined at the “8-digit” scale or as “HUC8s”. In this study, the repeated random utility model follows a two-level nesting structure, as depicted in Figure 1.2. In level 1, the set of sites is denoted as the choice set J = {1, ..., 64}. Sites in the set J_{Inland} = {1, ..., 38} are inland HUCs and sites in the set J_{GL} = {39, ..., 64} are Great Lakes HUCs along the shoreline. In level 2, individual *i* chooses whether to take a trip or stay at home.

Figure 1.1: Definition of Watersheds

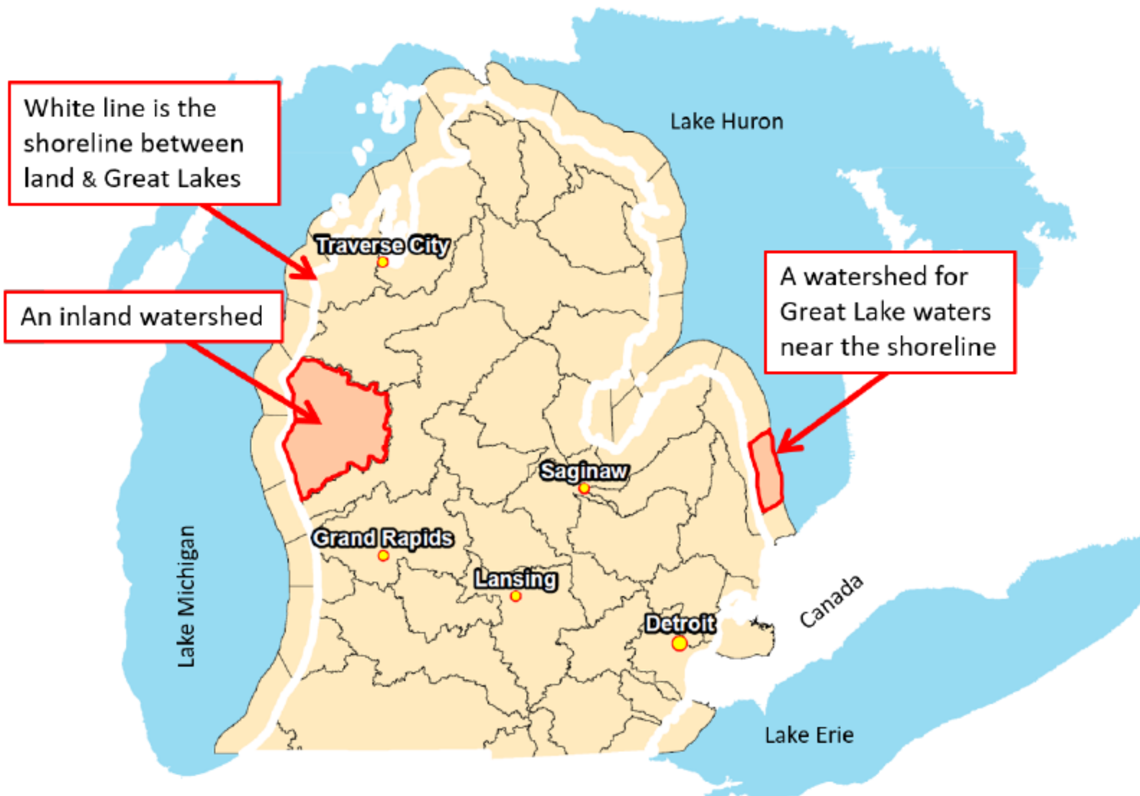
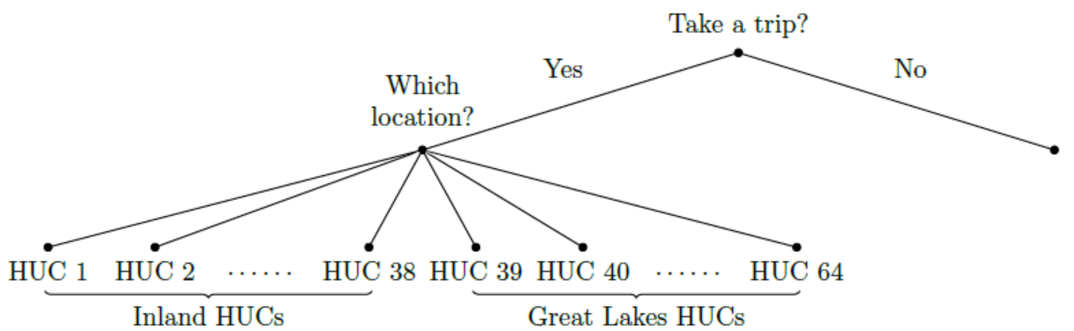


Figure 1.2: Nesting Structure



This is the planned nesting structure, but the current application only models inland HUCs 1 to 38.

Table 1.3 describes the summary statistics on the number of respondents who took trips in the last two years (2016-2018), the number of trips in 2018, and travel cost. The data also includes information on individual characteristics such as age, gender, education, and employment.

Table 1.3: Survey Sample Summary Statistics (N=3,770)

Variable	Sample Mean
Went_2yr (=1 if visted any)	0.86
Went_summer2018 (=1 if visted any)	0.71
Trips (times)	10.1
Single Day Trips (times)	7.7
Multiple Day Trips (times)	2.2
Travel Cost ($)	62.23
Median Income ($)	58,205
Gender (=1 if male)	0.27
Age (years)	45.5
Education (=1 if for college grad or higer)	0.56
Employment (=1 if full-time)	0.51
Fishing License (=1 if yes)	0.19

The variable *Went_2yr* is an indicator variable that takes on a value of 1 if the respondent visited any Michigan waterbodies within the past two years and 0 otherwise. Similarly, the variable *Went_summer2018* is also an indicator variable that takes on a value of 1 if the respondent visited any Michigan waterbodies during the summer of 2018, and 0 otherwise. The variable *Trips* represents the total number of trips by the respondent to Michigan waterbodies during the summer of 2018. *Single Day Trips* and *Multiple Day Trips* are variables that respectively represent the number of single-day trips and the number of multiple-day trips to Michigan waterbodies during the summer of 2018. The average cost of driving per person for a trip was \$62. The median total household income of sample respondents was \$58,205. Out of the total respondents, 27% were identified as males while the remaining respondents identified as females. The median age of the online panel was 45 years. The median value of each age group is chosen to represent the age of each respondent. The *education*, *employment*, and *fishing licenses* variables are dummy variables where the value is equal to 1 for college graduate or higher, 1 for full and part-time workers, and 1 for fishing license holders, and 0 otherwise. Of the total sample, 56% had a college degree or higher. 51% were employed either full or part-time, and 19% had a fishing license in Michigan.

The Travel Cost Model regards the number of trips to a site as the "quantity demanded" and the travel cost as the "price." Travel and time cost is a proxy for the price of a recreational trip (Haab & McConnell, 2002) and was specified as:

$$C_{ij} = \delta D_{ij} + v_i T_{ij} \tag{19}$$

where δ is the per-mile marginal driving cost of an average vehicle (27 cents per mile)[2]. Driving costs in each vehicle category are based on average costs for five top-selling 2018 models selected by AAA. This marginal cost includes fuel and maintenance as well as the marginal depreciation per mile (English et al., 2018; Lupi, Phaneuf, and von Haefen, 2020). D_{ij} is a round-trip distance to the destination j, v_i is the value of time, and T_{ij} is travel time for a round trip. To estimate time costs for individuals, I follow English et al. (2018) by taking one-third of the annual household income divided by 2,040 hours worked per year, where the one-third fraction is commonly used to reflect the that the time is for leisure travel.

To calculate the travel cost, travel distance and costs are calculated using the STATA command *georoute*, developed by Weber & Peclat (2017). Travel distance is the number of miles that one should drive by car to arrive at a destination from home. Two coordinates are required to calculate the travel distance. The centroids of individuals' zip codes and latitude and longitude coordinates of recreation sites are used. Travel

[2] The average marginal driving costs per mile (cpm) is 0.269, according to the 2018 AAA report on driving costs. AAA average cost per mile estimate for year 2018 can be found online: https://exchange.aaa.com/wp-content/uploads/2018/09/18-0090_2018-Your-Driving-Costs-Brochure_FNL-Lo-5-2.pdf

time is how long it takes to drive the latter distance under normal traffic conditions. Entrance fees and tolls are not considered in this analysis.

Zip code serves as a proxy for a point of departure, and the nearest site alternatives to the trip destination are assigned using the trip location. Respondents with missing zip codes are dropped from the sample as travel costs cannot be calculated. Additionally, individuals located outside of the Lower Peninsula of Michigan are also dropped from the survey because they fall outside of its scope. 94 of respondents reported that they reside in the Upper Peninsula. 229 of the total respondents who reported a trip to the Upper Peninsula were dropped from the sample. This is because the location of such trips cannot be matched to hydrologic units in the Lower Peninsula, and their inclusion of such trip points could negatively impact the accuracy of the estimation.

The dataset is suitable for our study for three reasons. Firstly, the Michigan survey collected recreational behavior data for the 2018 season, covering all lakes, rivers, and the Great Lakes in Michigan. Secondly, the empirical data structure allows us to explore two of our modeling approaches. Lastly, the water quality measures used in the same survey represent four different types of ecosystem services surrounding waterbodies, providing robust water quality attributes for each hydrologic unit. This allows us to examine the value of water quality, taking into account all the waterbodies in Michigan.

1.6. Results

Estimation results are based on revealed preference data collected from a Michigan resident online survey. The sample includes 3,190 respondents who met the sample selection criteria noted above.

Table 1.4 displays the estimated coefficients from the weighting model and the structural model for the sample described above, and the difference in the parameter estimates across models is relatively small. The travel cost coefficients are negative (-0.002) in all models with standard errors close to zero. The cost parameter estimate from structural model is 35% smaller than that from weighting model. As the travel cost for any site j increases, the indirect utility that a respondent gets from visiting that site diminishes, and demand for the site decreases.

Table 1.4: Empirical Model Estimates (J=38, T=60)

	Weighting Model Estimates	Structural Model Estimates
Travel cost coeff. (γ_c)	-0.0020 (0.0002)	-0.0027 (0.0002)
Nesting parameter (θ)	0.0840 (0.0065)	0.0930 (0.0054)
$WTP_{per\ trip}$ ($-\frac{\theta}{\gamma_c}$)	\$42.98 [\$42.38, \$43.58]	\$34.02 [\$32.40, \$35.77]

Note: Standard errors in parentheses and ASCs are reported in the appendix. Krinsky-Robb confidence interval is reported in brackets for the WTP measure.

All the estimated dissimilarity coefficients are small, which implies that in each case, unobserved utilities ε_{ijt} for the trip alternatives ($j = 1, \cdots, J$) are more correlated with each other than with the staying home option. The dissimilarity parameter estimate from structural model is 10% larger than that from weighting model. The dissimilarity coefficient θ of structural model is the largest.

For quick calculations of willingness-to-pay per trip ($WTP_{per\ trip}$) for access to a site, I can use a simplified form of the per-trip WTP function that is approximately correct when the share of trips to a site is small (Habb & McConnell, 2002).

$$WTP_{per\ trip} = -\frac{\theta}{\gamma_c} \tag{20}$$

The nonlinear combination of the cost coefficient $\widehat{\gamma_c}$ and the dissimilarity coefficient $\hat{\theta}$ implies the value per trip to most sites to be in a range between \$35 and \$42. The estimated mean WTP value from model 2 is accompanied by a 95% confidence interval, which ranges from \$42.38 to \$43.58. The estimated mean WTP value from model 3 is accompanied by a 95% confidence interval, which ranges from \$32.40 to \$35.77.

Alternative specific constant estimates are presented in the appendix (Table 1A.4). When interpreting the alternative specific constants, their relative magnitude is the only important factor to consider. The magnitudes of alternative specific constants α_j capture the average utility of a site's characteristics other than travel costs so that higher values have higher quality, all else equal.

1.7. Conclusion

Despite improvements in modeling and computing powers, there are inherent limitations on data available to analysts to model recreation demand. The preferred option is generally to use household-level information on recreation activities across a season (Freeman III et al., 2014). Often the survey design includes questions on detailed location for one trip along with the total number of trips to a group of sites. But compared to the ideal of complete trip information, analysts generally get only partial trip details answers at best (Parsons, 2017).

This paper develops two estimation approaches to address trip data challenges. One is to modify the likelihood function by weighting the number of trips to one reported site by the total number of trips during the study period. The advantage of the first approach is that it can be easily implemented in any standard nested logit statistical package using the estimation weights. The other method is to rewrite a censored likelihood function that separately identifies the choice probability to one specific location and correctly specifies the probability of taking a trip to any site for the trips with unknown locations. This modification of the likelihood function allows consistent and efficient maximum likelihood estimation based on the conditional distribution of the censored probability function, but the required specialized code means this model cannot be implemented in using existing nested logit packages. Our Monte Carlo experiments empirically confirm that both approaches for estimation with incomplete trip data are consistent and robust compared to true values and estimated values from a model with complete data.

Consistent with the Monte Carlo results, I find the proposed structural model for incomplete trips is empirically tractable with an actual survey dataset that includes incomplete trip information. The proposed structural model is used to analyze survey data on water-based recreation trips in Michigan. Model results from both empirical specifications (weighting and structural approaches) reveal statistically significant relationships between price and trips that are consistent with theoretical expectations. The demand results imply surplus values for a typical infrequently visited watershed of about $34 to $43 per trip. More frequently visited watersheds will have higher values.

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APPENDIX

Table 1A.1: List of Choice Alternatives defined by Inland HUCs

SiteID	HUC8	Name	AreaAcres	AreaSqKm
1	04040001	Little Calumet-Galien	561836	2273.67
2	04050001	St.Joseph	3016311	12206.59
3	04050002	Black-Macatawa	473504	1916.2
4	04050003	Kalamazoo	1300164	5261.58
5	04050004	Upper Grand	1126456	4558.61
6	04050005	Maple	605302	2449.57
7	04050006	Lower Grand	1305910	5284.83
8	04050007	Thornapple	543371	2198.95
9	04060101	Pere Marquette-White	2186965	8850.34
10	04060102	Muskegon	1745037	7061.92
11	04060103	Manistee	1254426	5076.49
12	04060104	Betsie-Platte	799029	3233.56
13	04060105	Boardman-Charlevoix	1206027	4880.62
14	04070003	Lone Lake-Ocqueoc	661855	2678.43
15	04070004	Cheboygan	572178	2315.52
16	04070005	Black	383992	1553.96
17	04070006	Thunder Bay	800137	3238.04
18	04070007	Au Sable	1311623	5307.95
19	04080101	Au Gres-Ri	837625	3389.75
20	04080102	Kawkawlin-Pine	314464	1272.59
21	04080103	Pigeon-Wiscoggin	672724	2722.42
22	04080104	Birch-Willow	300691.5	1216.86
23	04080201	Tittabawassee	926341	3748.77
24	04080202	Pine	656376	2656.26
25	04080203	Shiawassee	810027	3278.07
26	04080204	Flint	851488	3445.85
27	04080205	Cass	581022	2351.31
28	04080206	Saginaw	160795	650.71
29	04090001	St. Clair	956178.39	3869.52
30	04090002	Lake St. Clair	1451979.3	5875.96
31	04090003	Clinton	510131	2064.43
32	04090004	Detroit	676579.54	2738.02
33	04090005	Huron	587689.62	2378.3
34	04100001	Ottawa-Stony	632941.18	2561.42
35	04100002	Raisin	680354.68	2753.3
36	04100003	St. Joseph	699867	2832.26
37	04100006	Tiffin	497659	2013.96
38	07120001	Kankakee	1938433	7844.57

*Note that a choice set is defined by a list of inland HUCs using units of HUC8. HUC is an abbreviation of Hydrologic Unit Code.

Table 1A.2: Average Differences between True Values and Model Estimates (N = 3,500, J =38, T =60)

	True Value	Average Differences between True Values and Estimates		
		Model 1 *Full Data Model*	Model 2 *Weighting Model*	Model 3 *Structural Model*
α_1	-1.946	0.058	0.035	0.013
		(0.141)	(0.142)	(0.197)
α_2	-1.469	0.002	0.050	0.005
		(0.113)	(0.118)	(0.159)
α_3	-1.356	0.031	0.022	0.005
		(0.109)	(0.108)	(0.147)
α_4	-1.886	0.009	0.026	0.011
		(0.136)	(0.139)	(0.192)
α_5	-1.733	0.069	0.209	0.020
		(0.131)	(0.140)	(0.192)
α_6	-1.186	0.024	0.058	0.030
		(0.100)	(0.097)	(0.135)
α_7	-1.105	0.030	0.005	0.020
		(0.096)	(0.096)	(0.132)
α_8	-1.030	0.021	0.070	0.002
		(0.091)	(0.095)	(0.130)
α_9	-1.200	0.032	0.018	0.051
		(0.101)	(0.101)	(0.133)
α_{10}	-1.658	0.044	0.089	0.015
		(0.125)	(0.120)	(0.162)
α_{11}	-1.374	0.028	0.128	0.048
		(0.110)	(0.117)	(0.154)
α_{12}	-1.396	0.046	0.095	0.05
		(0.112)	(0.116)	(0.162)
α_{13}	-1.132	0.033	0.000	0.074
		(0.097)	(0.097)	(0.126)
α_{14}	-1.218	0.028	0.108	0.018
		(0.102)	(0.107)	(0.145)
α_{15}	-1.314	0.044	0.090	0.007
		(0.107)	(0.111)	(0.151)
α_{16}	-1.642	0.047	0.042	0.015
		(0.125)	(0.126)	(0.173)
α_{17}	-1.753	0.051	0.085	0.027
		(0.131)	(0.125)	(0.168)
α_{18}	-1.346	0.046	0.061	0.011
		(0.109)	(0.105)	(0.141)
α_{19}	-1.838	0.016	0.026	0.008
		(0.133)	(0.133)	(0.183)
α_{20}	-1.230	0.033	0.117	0.023
		(0.102)	(0.108)	(0.144)

Table 1A.2 (cont'd)

	True Value	Model 1	Model 2	Model 3
α_{21}	-1.534	0.021 (0.118)	0.115 (0.112)	0.072 (0.158)
α_{22}	-1.225	0.025 (0.102)	0.054 (0.099)	0.031 (0.131)
α_{23}	-1.363	0.029 (0.109)	0.125 (0.116)	0.007 (0.157)
α_{24}	-1.369	0.011 (0.109)	0.027 (0.108)	0.042 (0.149)
α_{25}	-1.131	0.02 (0.096)	0.035 (0.095)	0.012 (0.128)
α_{26}	-1.472	0.001 (0.113)	0.071 (0.111)	0.018 (0.152)
α_{27}	-1.174	0.023 (0.099)	0.097 (0.094)	0.013 (0.129)
α_{28}	-1.523	0.019 (0.117)	0.223 (0.130)	0.016 (0.177)
α_{29}	-1.124	0.03 (0.097)	0.027 (0.098)	0 (0.133)
α_{30}	-1.765	0.017 (0.130)	0.079 (0.135)	0.017 (0.184)
α_{31}	-1.954	0.017 (0.140)	0.093 (0.146)	0.006 (0.202)
α_{32}	-1.586	0.06 (0.122)	0.087 (0.126)	0.005 (0.171)
α_{33}	-1.977	0.068 (0.144)	0.139 (0.150)	0.002 (0.209)
α_{34}	-1.844	0.023 (0.134)	0.153 (0.127)	0.002 (0.172)
α_{35}	-1.779	0.04 (0.132)	0.02 (0.130)	0.022 (0.175)
α_{36}	-1.592	0.069 (0.123)	0.172 (0.131)	0.012 (0.180)
α_{37}	-1.391	0.042 (0.111)	0.153 (0.119)	0.008 (0.162)
α_{38}	-1.14	0.036 (0.098)	0.061 (0.101)	0.003 (0.136)
β_c	-0.4	0.003 (0.021)	0.006 (0.021)	0.003 (0.020)
θ	0.8	0.01 (0.042)	0.004 (0.043)	0.003 (0.046)

Table 1A.3: Average Differences between True Values and Model Estimates (N = 10,000, J =38, T =60)

	True Value	Average Differences between True Values and Estimates		
		Model 1 *Full Data Model*	Model 2 *Weighting Model*	Model 3 *Structural Model*
α_1	-1.102	0.003 (0.049)	0.032 (0.049)	0.010 (0.072)
α_2	-1.961	0.012 (0.073)	0.049 (0.074)	0.045 (0.107)
α_3	-1.608	0.017 (0.063)	0.009 (0.065)	0.014 (0.093)
α_4	-1.623	0.017 (0.063)	0.014 (0.065)	0.019 (0.093)
α_5	-1.831	0.002 (0.069)	0.015 (0.071)	0.002 (0.103)
α_6	-1.069	0.001 (0.048)	0.047 (0.048)	0.060 (0.069)
α_7	-1.704	0.010 (0.066)	0.033 (0.069)	0.027 (0.098)
α_8	-1.404	0.009 (0.057)	0.021 (0.060)	0.034 (0.085)
α_9	-1.095	0.001 (0.049)	0.051 (0.049)	0.050 (0.070)
α_{10}	-1.303	0.004 (0.054)	0.014 (0.056)	0.004 (0.080)
α_{11}	-1.849	0.000 (0.070)	0.047 (0.073)	0.028 (0.105)
α_{12}	-1.880	0.010 (0.071)	0.107 (0.076)	0.096 (0.110)
α_{13}	-1.700	0.016 (0.065)	0.006 (0.068)	0.005 (0.097)
α_{14}	-1.085	0.004 (0.048)	0.035 (0.051)	0.025 (0.073)
α_{15}	-1.620	0.016 (0.063)	0.047 (0.064)	0.033 (0.092)
α_{16}	-1.242	0.010 (0.053)	0.051 (0.056)	0.042 (0.079)
α_{17}	-1.947	0.014 (0.073)	0.008 (0.074)	0.002 (0.108)
α_{18}	-1.878	0.015 (0.071)	0.017 (0.073)	0.010 (0.106)
α_{19}	-1.492	0.003 (0.060)	0.032 (0.061)	0.031 (0.086)
α_{20}	-1.963	0.003 (0.073)	0.103 (0.078)	0.105 (0.115)

Table 1A.3 (cont'd)

	True Value	Model 1	Model 2	Model 3
α_{21}	-1.551	0.002 (0.061)	0.017 (0.063)	0.023 (0.091)
α_{22}	-1.199	0.002 (0.052)	0.049 (0.052)	0.029 (0.075)
α_{23}	-1.397	0.000 (0.057)	0.010 (0.059)	0.002 (0.084)
α_{24}	-1.331	0.008 (0.055)	0.004 (0.057)	0.025 (0.082)
α_{25}	-1.220	0.004 (0.052)	0.005 (0.054)	0.003 (0.077)
α_{26}	-1.700	0.008 (0.065)	0.049 (0.066)	0.045 (0.095)
α_{27}	-1.683	0.002 (0.065)	0.077 (0.069)	0.079 (0.099)
α_{28}	-1.701	0.004 (0.065)	0.008 (0.067)	0.008 (0.097)
α_{29}	-1.070	0.007 (0.048)	0.023 (0.049)	0.029 (0.070)
α_{30}	-1.551	0.009 (0.062)	0.051 (0.062)	0.035 (0.089)
α_{31}	-1.520	0.004 (0.060)	0.003 (0.062)	0.009 (0.088)
α_{32}	-1.068	0.006 (0.048)	0.02 (0.049)	0.022 (0.070)
α_{33}	-1.786	0.02 (0.067)	0.045 (0.069)	0.046 (0.098)
α_{34}	-1.117	0.003 (0.049)	0.088 (0.048)	0.062 (0.071)
α_{35}	-1.555	0.008 (0.061)	0.01 (0.064)	0 (0.090)
α_{36}	-1.336	0.006 (0.055)	0.119 (0.060)	0.111 (0.086)
α_{37}	-1.216	0.004 (0.052)	0.016 (0.054)	0.011 (0.077)
α_{38}	-1.646	0.013 (0.064)	0.025 (0.067)	0.042 (0.096)
β_c	-0.4	0.001 (0.011)	0.008 (0.011)	0 (0.012)
θ	0.8	0 (0.022)	0.005 (0.023)	0 (0.026)

Table 1A.4: Empirical Model Estimates (N=3,190, J =38, T =60)

	Model 2 *Weighting Model*	Model 3 *Structural Model*
α_1	-1.721	-1.669
	(0.014)	(0.020)
α_2	-1.706	-1.679
	(0.012)	(0.016)
α_3	-1.617	-1.553
	(0.007)	(0.011)
α_4	-1.706	-1.707
	(0.012)	(0.016)
α_5	-1.797	-1.781
	(0.019)	(0.019)
α_6	-1.913	-1.908
	(0.028)	(0.039)
α_7	-1.707	-1.651
	(0.012)	(0.014)
α_8	-1.931	-1.929
	(0.030)	(0.044)
α_9	-1.507	-1.415
	(0.008)	(0.015)
α_{10}	-1.573	-1.521
	(0.007)	(0.012)
α_{11}	-1.674	-1.609
	(0.011)	(0.021)
α_{12}	-1.493	-1.405
	(0.009)	(0.017)
α_{13}	-1.431	-1.338
	(0.013)	(0.018)
α_{14}	-1.464	-1.402
	(0.011)	(0.017)
α_{15}	-1.622	-1.559
	(0.009)	(0.024)
α_{16}	-1.701	-1.624
	(0.014_	(0.032)
α_{17}	-1.647	-1.625
	(0.010)	(0.030)
α_{18}	-1.596	-1.544
	(0.007)	(0.015)
α_{19}	-1.618	1.611
	(0.008)	(0.017)
α_{20}	-1.739	1.723
	(0.015)	(0.020)

Table 1A.4 (cont'd)

	Model 2 *Weighting Model*	Model 3 *Structural Model*
α_{21}	-1.680	-1.659
	(0.011)	(0.015)
α_{22}	-1.637	-1.619
	(0.008)	(0.013)
α_{23}	-1.686	-1.651
	(0.011)	(0.016)
α_{24}	-1.814	-1.749
	(0.021)	(0.025)
α_{25}	-1.846	-1.828
	(0.023)	(0.024)
α_{26}	-1.859	-1.845
	(0.024)	(0.024)
α_{27}	-1.99	-1.917
	(0.036)	(0.041)
α_{28}	-1.908	-1.868
	(0.028)	(0.031)
α_{29}	-1.796	-1.802
	(0.019)	(0.022)
α_{30}	-1.781	-1.787
	(0.018)	(0.016)
α_{31}	-1.847	-1.861
	(0.023)	(0.022)
α_{32}	-1.828	-1.835
	(0.021)	(0.019)
α_{33}	-1.799	-1.797
	(0.019)	(0.017)
α_{34}	-1.858	-1.853
	(0.023)	(0.023)
α_{35}	-1.841	-1.873
	(0.022)	(0.026)
α_{36}	-2.060	-2.020
	(0.045)	(0.071)
α_{37}	-1.863	-1.925
	(0.024)	(0.039)
α_{38}	-1.860	-1.922
	(0.025)	(0.070)

Essay 2: Testing the Robustness of a Structural Model for Discerning Use and Non-use Values of Ecosystem Services

2.1. Introduction

Economists define the benefits of environmental quality in terms of willingness to pay (WTP). The types of benefits are determined by the purpose for which the public are willing to pay. In a typical taxonomy of total economic values, use values involve direct enjoyment or consumption of ecological services, while non-use values involve benefits derived from the existence of an environmental amenity, independent of its present or future use. Leonard et al. (2021) point to biases toward direct uses in past rules governing public natural resources, which highlights the importance including both use and non-use values for efficient resource use and management.

To address this bias problem, this paper used Monte Carlo methods to examine a utility-theoretic structural approach designed to measure use and non-use values of non-market environmental resources. Specifically, we propose a structural estimation method that involves measures of use values and those of non-use values, by combining revealed preference and stated preferences from consequential referenda. For the revealed preference part where we derive demands from which to infer use values for environmental quality, we simulate individuals' recreational trip behavior and use their trip costs, the latter of which were estimated based on survey data collected in 2019. Then, with simulated stated preference data, we decompose the total value into use value and non-use value that people are willing to pay to improve environmental conditions of ecosystem services. In our conceptual framework, we choose a consequential, incentive-compatible, single-referendum contingent valuation method to elicit total WTP. Non-use WTP can be simultaneously and separately identified by the identification strategy we will introduce in the model section.

This approach is motivated by the policy demand and legal mandate that are required for public managed resources (Arrow et al., 1996), as well as practical concerns for research design (Smith et al., 2022) in ecosystem services valuation. U.S. Environmental Protection Agency calls for improving the measurement of non-use benefits for proposed rules in the regulatory impact assessment and benefit-cost analysis noting that there has been a limited number of studies that U.S. Environmental Protection Agency (EPA) could draw non-use benefit estimates from for regulatory decision-making (Griffith et al. 2012). Also, the structural approach in this paper can be applied further to estimate a complex package of ecological benefits derived from the quality changes of services that ecosystems provide. Building on the work by Day et al. (2019), we test the new method that combines a multi-site random utility recreation demand system with the referendum contingent valuation method. Unlike some *ad-hoc* proposals for measuring use and non-use values, this approach can estimate individuals' use WTP and non-use WTP portions of total value over a variety of choice alternatives within a single utility-theoretic approach.

In the model section, we define use and non-use utilities at the individual level and derive a formula for valuing use and non-use WTP. In doing so, we challenge the assumption sometimes appearing in the literature that users have only use values and non-users have only non-use values, especially since some empirical evidence shows that individuals hold both use and non-use values, regardless of their direct use of nature. Thus, we incorporate a theoretically consistent empirical framework as an alternative to ad-hoc approaches to define non-use values. Then, we present Monte Carlo simulations that compare the bias and root mean squared error (RMSE) of parameter estimates for different generated data. With the data generated from these experiments, we show the consistency of the empirical method. Simulation results show that the structural method is robust but has bias under certain conditions. The upshot is that researchers pursuing this approach should be cautious with its power if they have preliminary data or priors that non-use values are small relative to use values, as our simulations show those cases are prone to some bias, whereas bias is small for a broad range of cases. We conclude the paper with a discussion of the limitations of this research and some future research topics.

2.2. Literature and Background

Non-market valuation is a tool for economic valuation of ecosystem services based on a link between changes in the quantity or quality of the resource and the changes in the stated or observed behavior of people. The measurement of this relationship facilitates the comparison of values of non-market goods in monetary units. For example, contingent valuation studies have been used to assess the damages to waterbodies caused by accidents such as oil spills and inform administrative and judicial decisions (Bishop et al., 2017; Carson et al., 2003; English et al., 2018; Loomis, 1997). Use and existence values of environmental quality changes can be measured in a hypothetical market, consistent with economic theory, and they can be used as a starting point for resource management decision of government agencies (Carson, 2012; Kling et al., 2012).

Of the myriad benefits that the natural environment provides, some of the values are relatively straightforward to measure through revealed market transactions (Arrow et al., 1993). For example, use values are reflected in observed behavior of individuals who actively use natural resources (recreational fishers, boaters, swimmers, hikers, and others). Individuals use environmental amenities to enhance their welfare by producing utility yielding goods or services, or by using them as substitutes for, or complements to, market goods such as recreation trips (Freeman III et al. 2014). Non-use values, however, are independent of a person's present or future use of the resource. Broadly defined, non-users are individuals who do not use a particular site but may derive utility from its existence or for others' use. Although alternative views exist on the definition of, classification of, and boundary between use and non-use values, Smith (1987) conceptualizes non-use benefits as option and existence value, the latter of which includes bequest value.

A key challenge that arises in estimating the benefits is to conceptualize non-use values and distinguish them from use values, where it is the combined use and non-use values that sum to the total economic value of resources. This is especially important for meta-analyses of values seeking to isolate the value types and for filling in gaps in literature in other areas where it becomes useful to draw upon ratios of use and non-use found in the literature (Griffiths et al., 2012). Yet, at times a fuzzy definition of use and non-use values prevails in literature and makes it difficult to select a legitimate empirical model to determine non-use values. Some of various methods to measure non-use value are reviewed and discussed by Johnston et al. (2003).

A common ad hoc approach to define use and non-use is to treat use values as the value held by users and non-use values as the values held by non-users and compare total willingness to pay (WTP) for non-users with total WTP for users. For example, Croke, Fabian and Brenninam (1987) classify survey respondents who currently use rivers as users and find that the mean willingness to pay for water quality improvements is higher among users than non-users. Whitehead et al. (1995) find the WTP of on-site users are greater than WTP of off-site users or WTP of non-users when comparing WTP of three groups (on-site users, off-site users, and non-users). Similarly, Bockstael, McConnell and Strand (1989)'s contingent valuation survey results show that users are more willing to pay a tax for water quality improvements in the Chesapeake Bay, with the sample comprised of 43% users and 57% non-users. Whittington et al. (1994) also find that a typical user of Galveston Bay is more likely to support the plan for environmental quality improvement than a typical non-user. A shortcoming of this approach is that it could imply users do not have non-use values. Even the definition of "users" differs across studies. Some papers define users as visitors and non-users as non-visitors. Similarly, users may have non-use values for other recreation alternatives that they do not use. Non-users in a specific time period may hold use values for any resource at different places and times.

Another method that has been used in previous literature is to compare the WTP for different purposes: use purposes and non-use purposes. Lant and Roberts (1990) let the WTP for recreational use represent use values and the WTP for intrinsic values be non-use values. They find that non-use value benefits of river quality improvement exceed the benefits for direct use. Other studies rely on the respondent's decomposition of values into categories of use and non-use values (Roberts and Leitch 1997). For example, after respondents report their total, a follow up question would ask them to apportion the total WTP into use, option, and existence values categories (Kaoru, 1993; Sanders et al., 1990; Sutherland & Walsh, 1985).

A few examples venture to estimate non-use values as the total WTP of a survey sample who were asked to assume they would not use the resource being valued. Magat et al. (2000) examine the rate of tradeoff between water quality improvements in the person's own region versus water quality improvements in a region that the respondent will not visit. They also analyze the potential values of water quality based on the probability that the respondent will visit another region. This type of research design attempts to take non-use and probabilistic use values into account.

More recently, researchers have devised more delicate survey designs and estimation strategies as methods evolve. Under a combined revealed and stated preference setting, the models estimate non-use values as total WTP of the sample of users minus estimated WTP for the direct use of the resource estimated based on revealed preference data (Eom and Larson 2006; Whitehead et al. 2008; Egan 2011). Landry et al. (2020) jointly estimate models of beach recreation demand and total WTP. They find evidence of significant welfare gains from beach erosion control policies that affect beach width and coastal environmental quality with a large component for existence values.

2.3. Structural Model of Use and Non-use Values

The objective of the econometric model that is introduced here is to simultaneously estimate use and non-use values using both simulated RP and SP data (Day et al., 2019). In this paper, the conceptual framework incorporates a single dichotomous contingent valuation question into a random utility recreation demand model, rather than repeated choice experiments as used in Day et al. (2019). We use a single referendum question because the approach is consequential and explore its abilities to identify the distinction of use and non-use values since a single question is less efficient than a panel of responses for each individual. The RP portion of the model uses a repeated RUM approach that captures total trips and site allocations (Freeman III et al. 2014) and incorporates a full set of site-specific constants. For each individual *i* choosing site *j* with the state of environmental quality *s* at each choice occasion *t*, the joint conditional indirect utility function can be specified in an additively separable form.

$$u_{i,t,s|j} = v_{i,t,s|j}^{Use} + v_{i,t,s}^{NonUse} + v_{i,t,s|j}^{other} + \varepsilon_{i,j,t,s} \tag{1}$$

where the first term on the right-hand side is the conditional indirect utility from recreation activities at site *j* and the second term is the non-use utility gain from J different sites, independent of the recreation activity, and the third term is the utility from a composite good. All the conditional indirect utility terms besides the errors are constant over choice occasions, which will substantially simplify some terms below. The error terms are allowed to vary over choice occasions.

When individual *i* evaluates the option of visiting visit site *j* on a choice occasion t, the conditional use utility of visiting site *j* among J sites is a linear combination of alternative specific constant α_{ijt} and site quality q_{js}. When individual *i* evaluates the option to "not go" to any site at a choice occasion at *t*, the conditional use utility for such opt-out choice *J+1* does not include quality and is given by $\alpha_{i,J+1,t}$.

$$v_{i,t,s|j}^{Use} = \begin{cases} \alpha_{ijt} + q_{js}\beta & \text{if } j = 1, 2, \dots, J \\ \alpha_{i,J+1,t} & \text{if } j = J+1 \end{cases} \tag{2}$$

Non-use utility is characterized by the distance weighted sum across all the non-use utility gained from sites *j = 1* to *J* as follows:

$$v_{i,t,s}^{NonUse} = \sum_{j=1}^{J} \left(d_{ij} + 1\right)^{\lambda} \left(a_{ijt} + q_{js}b\right) \tag{3}$$

where λ_i is a parameter of the rate of distance decay in non-use utility. The value of λ determines how non-use utility may change with respect to distance.

Finally, the conditional utility from other consumption at choice occasion *t* is assumed to be linear in expenditure.

$$v_{i,t,s|j}^{other} = \gamma(y_{i,t} - p_{i,j} - c_s) \tag{4}$$

where γ is a parameter of the marginal utility of money and $y_{i,t}-p_{i,j}-c_s$ is the expenditure available for other goods. Note that $p_{i,j}$ is a travel cost of individual *i* for visiting site *j* and c_s is the per-occasion lump-sum cost from the referendum for environmental quality change.

2.3.1. Revealed Preference Portion of the Structural Model (RP-only Model)

To simulate travel cost data, we assume the trips occur in the baseline period (i.e., without environmental quality change, $q_{j,0}$). Under the current environmental condition (s = 0), there is no fee so $c_{i,0} = 0$ for all *i*. In this case, the probability that individual *i* will choose trip alternative *j* on choice occasion *t* is given by:

$$\begin{aligned} Pr_{i,j,t,0} &= Pr\left(u_{i,t,0|j} - u_{i,t,0|k} > 0\right) \\ &= Pr\left[\left(v_{i,0|j}^{Use} + v_{i,0}^{NonUse} + v_{i,0|j}^{other}\right) - \left(v_{i,0|k}^{Use} + v_{i,0}^{NonUse} + v_{i,0|k}^{other}\right) \right. \\ &\qquad \left. > \varepsilon_{i,k,t,0} - \varepsilon_{i,j,t,0}\right] \end{aligned} \tag{5}$$

for all $k \neq j \in \{1, \cdots, J\}$. Non-use utility $v_{i,0}^{NonUse}$ cancels out of the per-choice occasion trip probabilities as it is constant for each individual *i* at choice occasion *t*, i.e., an individual's trip decision is not influenced by non-use values.

We normalize the no trip utility to zero because only the difference between the trip utilities of choice alternatives matters in discrete choice models.

$$\begin{aligned} Pr_{i,j,t,0} &= Pr\left(u_{i,t,0|j} - u_{i,t,0|k} > 0\right) \\ &= Pr\left[v_{i,0|j}^{RP} - v_{i,0|k}^{RP} > \varepsilon_{i,k,t,0} - \varepsilon_{i,j,t,0}\right] = Pr_{i,j,0} \end{aligned} \tag{6}$$

2.3.2. Adding SP Data with Non-Use Values to the Structural Model (Joint RP-SP Model)

Next, we add simulated SP data with both use and non-use values in the model. The annual joint utility that individual *i* receives from choosing from a state of the world *s* (*s* = 0, 1) is

$$u_{i,\cdot,s} = \tilde{v}_{i,\cdot,s} + \tilde{\varepsilon}_{i,\cdot,s} = \sum_{t=1}^{T} \tilde{v}_{i,s} + \sum_{t=1}^{T} \tilde{\varepsilon}_{i,s} = T\tilde{v}_{i,s} + \sum_{t=1}^{T} \tilde{\varepsilon}_{i,s} \tag{7}$$

where the deterministic term of the annual utility is the expected maximum utility per choice occasion times the number of choice occasions.

The expected maximum joint utility of each individual *i* receiving use value from taking trips and non-use under a state of the world *s* can be written as

$$\tilde{v}_{i,s} = \mathbb{E}\left[\max_{j \in \{1,2,\cdots,J+1\}} \left(v_{i,s|j}^{Use} + v_{i,s|j}^{other} + \varepsilon_{i,j,t,s}^{Use}\right)\right] + \frac{v_{i,0}^{NonUse}}{\sigma^{SP}} \tag{8}$$

For specification of the trip-taking random utility model, the errors $\varepsilon_{i,j,t,s}^{Use}$ are assumed to follow a Type 1 Extreme value error term with a scale factor of σ^{RP}, which is not separately identified in conditional logits and is normalized σ^{RP} to be 1. While $\varepsilon_{i,j,t,s}^{Use}$ has a *t* subscript, the expectation does not depend on *t* since the $\varepsilon_{i,j,t,s}^{Use}$'s are identically distributed over time. Following assumptions made in Day et al. (2019) paper, the joint use and non-use utility function takes a log sum form, plus a constant κ.

$$\tilde{v}_{i,s} = \frac{1}{\sigma^{SP}} \ln\left[\sum_{j=1}^{J+1} \exp\left(v_{i,s|j}^{Use} + v_{i,s|j}^{other}\right)\right] + \kappa + \frac{v_{i,0}^{NonUse}}{\sigma^{SP}} \tag{9}$$

where κ is a constant of integration for the expected value of a maximum of extreme values (Johnson and Kotz, 1969). The scale parameter σ^{SP} characterizes the relative variation in the SP data compared to the RP data. From empirical studies in the literature, we expect SP data to show greater variability than RP data (i.e., σ^{SP}> 1).

Then, we can derive the choice probability that individuals would choose the proposed quality change scenario (*s* = 1) in terms of the difference between joint utilities before and after the change.

$$Pr\left(u_{i,\cdot,1} > u_{i,\cdot,0}\right) = Pr\left(\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0} > \tilde{\varepsilon}_{i,\cdot}\right) \tag{10}$$

To derive the choice probability of individuals choosing the quality change scenario (*s* = 1) compared to the baseline environmental condition (*s* = 0), kappa is the same in $\tilde{v}_{i,\cdot,1}$ and $\tilde{v}_{i,\cdot,0}$ and cancels out. This choice probability can be rewritten as the cumulative distribution function for the difference in errors $\widetilde{\epsilon_{\iota,.}} = \tilde{\epsilon}_{i,t,0} - \tilde{\epsilon}_{i,t,1}$. Assuming that $\widetilde{\epsilon_{\iota,.}}$ follows a logistic distribution of (0, 1), the difference in error term $\widetilde{\epsilon_{\iota,.}}$ approximately follow a t-distribution $t_{5T+4}(0,\tau)$ where $\tau = \pi\left(\frac{15T+12}{5T^2+2T}\right)^{-\frac{1}{2}}$ (George and Mudholkar, 1983; Day et al., 2019).

The resulting likelihood function characterizes individual *i*'s revealed preference for recreational sites along with their stated preference choices when choosing the sites to visit and the vote to make in the referendum. Specifically,

$$L_i(\boldsymbol{\theta}_i) = \prod_t \prod_j Pr_{i,j,t}\left(\boldsymbol{\theta}^{\boldsymbol{Use}}, \gamma\right)^{Y_{i,j,t}} \prod_s Pr_{i,s}\left(\boldsymbol{\theta}^{\boldsymbol{Use}}, \boldsymbol{\theta}^{\boldsymbol{NonUse}}, \gamma\right)^{Y_{i,s}} \tag{11}$$

where $\boldsymbol{\theta} = \left[\boldsymbol{\theta}^{\boldsymbol{Use}}, \boldsymbol{\theta}^{\boldsymbol{NonUse}}, \boldsymbol{\lambda}\right]$ are parameters of interest in the structural model of use and non-use values. $\boldsymbol{\theta}^{\boldsymbol{Use}} = \left[\alpha_1, \dots, \alpha_J, \beta\right]$ denote the parameters of the use utility, and $\boldsymbol{\theta}^{\boldsymbol{NonUse}} = [b, \lambda]$ denote the identifiable parameters of the non-use utility. The maximum log-likelihood estimation program solves

$$L_{SP} = \log\left(L_i(\boldsymbol{\theta}_i)\right) = Y_i^{SP} \ln\left[F_{\tilde{\varepsilon}}\left(\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0}\right)\right] + \left(1 - Y_i^{SP}\right) \ln\left[1 - F_{\tilde{\varepsilon}}\left(\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0}\right)\right] \tag{12}$$

Once we have estimated parameters, we can compute welfare measures. Since researchers do not observe true utilities, welfare changes are taken using expectations of outcomes from the random utilities with and without a change (Freeman III et al. 2014). The per choice occasion willingness to pay for the use benefits from the policy change takes the form

$$WTP^{Use} = \frac{1}{\gamma} ln[\frac{\sum_{j=1}^{J+1} \exp{(\widetilde{\alpha_j} + \Delta_{i,j,1}\beta - \gamma p_{i,j})}}{\sum_{j=1}^{J+1} \exp{(\widetilde{\alpha_j} - \gamma p_{i,j})}}] \tag{13}$$

where the marginal use utility divided by the marginal utility of money (γ) and Δ represents a change in quality. Likewise, the per choice occasion willingness to pay for the non-use benefits from the environmental quality change is calculated by the change in non-use utility. The division by γ translates utility into dollars and yields

$$WTP^{Nonuse} = \frac{1}{\gamma} \ln\left[\sum_{j=1}^{J} \left(d_{i,j} + 1\right)^{\lambda} \Delta_{i,j,1} b\right] \tag{14}$$

2.4. Monte Carlo Simulation

This section evaluates the performance of the structural estimation program to measure use and non-use values for improved environmental quality. We follow the modeling procedures to generate the data and set up the maximum likelihood function. We first estimate the structural model assuming that the non-use component of overall utility is zero. We then incorporate a non-use component into overall utility. The primary reason for the Monte Carlo simulation is that given the single SP observation per person, the full set of recreation site-specific fixed effects, and the highly nonlinear nature of the model and the corresponding log-likelihood function, the Monte Carlo exercise provides potentially useful insights into difficulties one might encounter in estimating the structural model, including potential problems with identification or local optima. This will be useful for future valuation efforts in considering whether to apply the method.

2.4.1. Monte Carlo Simulation Set-Up

The key idea of the Monte Carlo (MC) exercise is to generate simulated data to estimate two models in sequence: (1) a discrete choice random utility model of recreation demand based on the revealed preference portion of the structural model (i.e., RP model) for starting values and (2) a joint revealed and stated preference model for use and non-use values (i.e., joint RP-SP model). Portions of the simulated data are drawn to represent the types of preferences and range of some of some existing studies. The data is also drawn using information from the survey used in Lupi et al. (2023) and is designed to mimic some characteristics of a general population survey which will be used in a future empirical application (the survey was recently used in Sandstrom-Mistry et al., 2023).

After drawing simulated data, the algorithm uses GAUSS's maximum likelihood routine to estimate a repeated random utility maximization (RUM) model using revealed reference data alone. This program estimates the alternative specific constants (ASCs), which are site-specific fixed effects for the site attributes, and the parameter of marginal utility of income given by the negative of the parameter on travel costs to each site. Then, those parameters are used as initial values in the joint estimation of the structural model of use and non-use values. Specifically, the program uses the joint log-likelihood function and both simulated RP and SP data to estimate the marginal use utility of environmental quality improvement (β), the marginal non-use utility of environmental quality improvement (b), the distance-decay parameter (λ), and the scaling factor for the variation of error terms (σ), as well as updating the ASCs (α's) and the marginal utility of income parameters (γ).

In conducting the Monte Carlo exercise, we consider a variety of parameter configurations defined in terms of alternative levels for β, b, and σ. For each of these parameter combinations, the MC exercise proceeds in seven steps reported in Table 2.1. In addition, the MC exercise produces mean and median estimates of the parameters of interest and their 90% confidence interval. It also calculates four key variables: (1) the implied stay-at-home probabilities under the proposed parameter configuration, (2) the implied average probabilities of responding yes to the SP scenario for environmental quality change, (3) willingness to pay (WTP) for the use benefits from the scenario, and (4) WTP for the non-use benefits from the scenario. For each of these, minimum, mean, and maximum values are reported.

Table 2.1: Monte Carlo Steps for Each Parameter Configuration {β, b, and σ}

Step	Description
Step 1	The basic characteristics of the Monte Carlo exercise are set - The number of observations (N) - The number of choice alternatives (J) - The number of choice occasions (T) - The number of Monte Carlo replications (R) We chose R=1,000 so that the program simulates 1,000 different datasets and goes through 1,000 iterations of estimation under each specification.
Step 2	True values for the parameters are set to be constant within each of the 1,000 iterations
Step 3	For each iteration (r = 1, …, R), we draw random values for travel costs, the changes in environmental quality under the proposed scenario and the cost.
Step 4	The RP site choice utilities and probabilities for the underlying RUM model of recreation demand are computed for each individual and used to draw site the simulated choice decisions for each individual on each choice occasion.
Step 5	The RP site choices are used to estimate the parameters of the RP RUM model for use as starting values of the joint estimation.
Step 6	The SP choice probabilities based on the use and non-use values are computed for each individual following the structural model and used to draw their dichotomous choice response to the proposed scenario.
Step 7	The SP choice outcomes, together with the RP site choices, are used to jointly estimate the alternative specific constants, the marginal utility of income parameter, and three sets of additional parameters: the marginal use utility of environmental quality, the marginal non-use utility of environmental quality, and the scaling factor.

Table 2.2 presents the design for some of the levels used in the Monte Carlo analyses. The design is intended to cover a range for relative use and non-use values similar in spirit to the mixed results found in the literature.

Table 2.2: Monte Carlo Design

Experiment Design	A Set of True Values or the True Value	Number of Variants
Number of observations	N= {2,000, 5,000}	2
Marginal utility of money	γ= -0.4	1
Marginal use utility of environmental quality	β = {0.1, 0.2}	2
Marginal non-use utility of environmental quality	b = {0.05, 0.1, 0.2, 0.3, 0.4}	5
Scale parameter	σ = {2, 3}	2
Distance decay parameter	λ = -1	1
	Total	40

Additional details and rationale for the Monte Carlo design follow:

- Number of observations (N): Since the sample size of some valuation studies focusing on environmental resources is around 300 for smaller studies (Caudill et al., 2011), about 2,000 for many studies (Melstrom et al. 2015; Knoche and Lupi 2007; Kotchen et al. 2006), with only a few national-level studies gather samples with more than 10,000 observations (English et al., 2018; Day, 2020), we use 2,000 to represent common empirical studies. To ensure that estimators of parameters converge in probability to the true value of each parameter, simulations were also run with larger sample size (N=5,000), in which case the magnitude of bias diminished. The simulation results implied the structural method generally preserves the consistency of estimator.
- Number of recreational sites (J): we set the number of sites to be 38. We also tested the estimation routine and found similar results in a setting with a small number of sites, as well as a larger number of sites.
- Number of choice occasions (T): In recreation demand literature, a sufficiently large number, and sometimes the maximum number of trips taken during the study period, is typically chosen for the number of choice occasions to avoid trimming the trip data. Here we choose T = 30 to match a typical study for summer trips (Lupi et al., 2022).

- The travel costs (p_{ij}): Travel costs were randomly drawn from an existing survey sample trip data set that contain residence locations, site travel distances, site travel times, incomes of Michigan residents (Lupi et al., 2023). The cost of not taking a trip is zero for everyone. In the simulation, travel costs are drawn independent of unobserved site characteristics.
- The marginal utility of income parameter (γ): In our MC exercise we set γ to be −0.40. Initial values for this parameter value are estimated from a logit recreation demand model, in which the travel cost parameter is estimated using revealed preference data from other survey data (Kim et al., 2023).
- Alternative specific constants (ASCs): The ASCs are set to ensure that the average probability that an individual will stay at home on a given choice occasion (i.e., $\text{Prob}_{i,J+1}$) is approximately 0.17, which amounts to about 5 trips per person per year based on other existing survey data (Lupi et al., 2023). These site-fixed effects are assumed to be the same for all individuals. We use a full set of fixed effects (ASCs) for each of the J sites in the Monte Carlo exercise.
- Proposed stated preference scenarios: The simulation scenarios vary parameter configurations along two dimensions: the change in environmental quality improvement (Δq), and the contingent valuation cost levels (C). The change in environmental quality at each site is drawn randomly in the range of 0 to 10. The value for the change in environmental quality is heterogeneous across individuals. That mimics the experimental design in recent contingent valuation setting, where individuals face different scenarios of one proposed environmental quality improvement and corresponding cost (Sandstrom-Mistry et al., 2023). In Monte Carlo simulation exercise, the contingent valuation cost level is also drawn randomly across individuals. The range of the contingent valuation scenario cost is [0, 50] per choice occasion. It means that individuals agree to pay the per choice occasion policy cost if individuals decide to vote for a proposed environmental quality change.

- Scaling Parameter (σ): Estimation of the joint RP-SP model provides estimates of the common parameters along with any RP-specific and SP-specific model parameters. A "scale" parameter represents the relative scale of the coefficients of the RP-only model and joint RP-SP model since the variances of the random components of the RP and SP utility functions are likely to differ (Ben-Akiva et al., 1994). The scale parameter was set at $\sigma = [1, 2, 3]$ with the one implying equal variance in the RP and SP data and the larger levels mirroring or exceeding levels found in other studies, such as Day et al. (2019).
- Distance (d_{ij}): Distance is the straight-line distance from an individual's home to trip destination j. In the simulation, we set this straight-line distance to be a random proportion of travel cost based on an examination of existing data. We set the non-use distance decay parameter λ to a negative value (i.e., $\lambda = -1$) as is often found in the literature. It means that sites closer to an individual's home have more non-use value than more distant sites. That is, the non-use utility from improved environmental quality benefits at site j diminishes as individuals live far from the site.

2.4.2. Monte Carlo Simulation Results

The RP-only model estimation produces the estimates of common parameters: the parameter estimates of alternative specific constants (each α_j) and the marginal utility of income (γ). The joint RP-SP model adds four additional parameters to those identified in the RP-only model: marginal use utility of environmental quality (β), marginal non-use utility of environmental quality (b), a non-use distance decay (λ), and a scaling factor (σ). We summarize the result of the Monte Carlo simulation experiments and compare four tables for the generalized structural RP-SP model in this section.

In this section, we primarily focus our attention on the two environmental quality parameters (β and b) to check the model performance when estimating the key parameters of interest (Table 2.3). Then, in the second table (Table 2.4), we investigate the extent of estimation errors on the travel cost parameter (γ) and the alternative specific constants (each α_j) as they are also key determinants of welfare measures. Both tables include the root mean square errors (RMSEs) and percentage RMSEs results for two versions of joint RP-SP models. In the first sub column, denoted as "λ fixed," the distance decay parameter λ is fixed as a constant at the true level and is not estimated. The second sub column, denoted as "λ est.," estimates the distance decay parameter.

Table 2.3 presents true values of key parameters of interest (β, b, σ, λ), root mean squared error (RMSE) and the percentage root mean squared error (%RMSE) of estimates of each parameter. The first three columns are true values. The latter columns compare RMSE and %RMSE of two models. Compared to the RMSE of the Use Quality parameter estimates, the RMSE of the Non-Use Quality parameter estimates is slightly larger in both "λ fixed" and "λ est." models. The same is true for %RMSE. It implies that the Use Quality parameter is more precisely estimated than the Non-Use Quality parameter or the Scaling factor parameter. Both RMSE and %RMSE values are larger when λ is estimated than when λ is known. The magnitude of RMSE and %RMSE of the distance decay parameter diminish as the true value of the Non-Use Quality parameter estimates increases. When the marginal utility gain from the non-use portion is particularly large, the distance decay effect seems to be more easily detected.

There are some notable findings we can draw from the simulations. First, the joint RP-SP approach with constant distance decay parameter (λ fixed) successfully recovers the underlying use and non-use quality parameters, with a root mean squared error of 0.03. However, converting RMSEs into the % RMSE terms, we find the %RMSE of use quality parameter increases as the true value of the non-use quality parameter increases. Conversely, the %RMSE of non-use quality parameter decreases as the true value of the non-use quality parameter increases.

Second, the joint RP-SP model that estimates a distance decay parameter (λ est.) also performs quite well on estimating the use quality parameter, with a root mean squared error less than 0.02 for ($\hat{\beta}$). However, it does not do as well on estimating non-use quality parameter ($\hat{b}$) or scaling factor ($\hat{\sigma}$), particularly when the true value of the non-use quality parameter is very small. Adding additional dimension into the model by estimating the distance decay parameter results in 10 times larger %RMSE.

Table 2.3: Monte Carlo Simulation Results – Key Parameter Estimates of Interest

				Root Mean Squared Error							
				(1)		(2)		(3)		(4)	
True β	True b	True σ	True λ	UseQuality $\hat{\beta}$		Non-use Quality $\hat{b}$		Scaling Factor $\hat{\sigma}$		Distance Decay $\hat{\lambda}$	
				λ fixed	λ est.	λ fixed	λ est.	λ fixed	λ est.	λ fixed	λ est.
0.2	0.05	2	-1	0.02	0.02	0.03	2.01	0.13	3301.79	NA	1.01
0.2	0.1	2	-1	0.02	0.02	0.03	1.89	0.07	1.98	NA	1.05
0.2	0.2	2	-1	0.01	0.02	0.03	1.66	0.11	1.90	NA	0.24
0.2	0.3	2	-1	0.02	0.03	0.03	1.56	0.14	1.79	NA	0.15
0.2	0.4	2	-1	0.03	0.04	0.04	1.51	0.15	1.65	NA	0.10
				% Absolute Root Mean Squared Error							
				λ fixed	λ est.	λ fixed	λ est.	λ fixed	λ est.	λ fixed	λ est.
0.2	0.05	2	2	8.02	11.11	64.17	4011	6.42	165,089	NA	-101.27
0.2	0.1	2	2	8.47	9.42	33.21	1868	3.55	99.23	NA	-104.80
0.2	0.2	2	2	7.30	10.27	14.85	829.43	5.54	94.85	NA	-24.02
0.2	0.3	2	2	10.02	16.69	8.98	519.28	6.76	89.36	NA	-15.15
0.2	0.4	2	2	14.49	19.42	9.22	376.47	7.31	82.53	NA	-10.33

* All runs with sample set at N=2,000 using R=1,000 replications

Table 2.4 provides the root mean squared error (RMSE) and the percentage root mean squared error (%RMSE) of estimates of three alternative specific constants (ASCs) and the marginal utility of income (cost) parameter γ. As in Table 2.3, assumed true values of two key parameters of interest (β, σ) remain unchanged while we vary the marginal non-use utility of quality changes (b). Of J=38 alternative specific constants, column (1) reports the RMSE and %RMSE values of the minimum ASC; column (2) reports them for the median ASC; and column (3) reports them for the maximum ASC. Starting with the results for the travel cost coefficient in the column (4), both joint RP-SP models (with λ fixed and λ est.) do an excellent job recovering the underlying price coefficient, with the root mean squared error less than 0.001, perhaps to the variation across people and sites that exists for travel costs. The models also do a good job in recovering the underlying alternative specific constants (ASCs), regardless of the magnitude of the ASCs.

Table 2.4: Monte Carlo Simulation Results – Site Fixed Effects and Cost coefficient

			Root Mean Squared Error							
			(1)		(2)		(3)		(4)	
True β	True b	True σ	min (ASC26)		median (ASC19)		max (ASC35)		Cost $\hat{\lambda}$	
			λ fixed	λ est.	λ fixed	λ est.	λ fixed	λ est.	λ fixed	λ est.
0.2	0.05	2	0.01	0.01	0.05	0.05	0.03	0.03	6E-05	6E-05
0.2	0.1	2	0.01	0.01	0.05	0.05	0.03	0.03	6E-05	6E-05
0.2	0.2	2	0.01	0.01	0.05	0.05	0.03	0.03	6E-05	6E-05
0.2	0.3	2	0.01	0.01	0.05	0.05	0.03	0.03	6E-05	6E-05
0.2	0.4	2	0.01	0.01	0.05	0.05	0.03	0.03	6E-05	0.00
			% Absolute Root Mean Squared Error							
			λ fixed	λ est.	λ fixed	λ est.	λ fixed	λ est.	λ fixed	λ est.
0.2	0.05	2	0.68	0.67	1.92	1.95	1.07	1.06	0.32	0.31
0.2	0.1	2	0.68	0.66	1.93	1.93	1.07	1.07	0.32	0.31
0.2	0.2	2	0.67	0.66	1.92	1.92	1.07	1.07	0.31	0.30
0.2	0.3	2	0.67	0.67	1.91	1.92	1.08	1.07	0.32	0.31
0.2	0.4	2	0.67	0.67	1.92	1.93	1.07	1.07	0.31	0.31

* All runs with sample set at N=2,000 using R=1,000 replications
* True λ is -1 for all cases.

The root mean squared error remains very low in all cases and the % absolute RMSE also very small regardless of the true values of parameters of the interest. Although we report only the results of three ASCs, no obvious relationship has been found between the magnitude of true ASCs and their RMSEs/%RMSEs for each of the ASCs. Across different parameter spaces, the RMSE and %RMSE of ASCs and the cost parameter remain at similar levels. It implies that ASCs and the cost parameter estimation are quite stable across various true values of the Non-Use Quality parameter. While the overall use and non-use model is not mean fitting for site choices, that property would hold for the use value portion of the use value only portion of the joint utility, so it is perhaps unsurprising that the approach replicates the ASCs well.

Table 2.5 reports the difference between the medians of true WTP and WTP estimates. We find that the magnitude of the WTP estimates is similar to that of true WTP when we evaluate at the median of the estimated parameters. The distribution of WTP estimates also remains close to the true distribution of WTP.

Table 2.5: Difference between Median WTP Estimates and Median True WTP ($'s)

True β	True b	True σ	True λ	Difference in Use WTP ($)	Difference in Non-use WTP ($)	Difference in Total WTP ($)
0.2	0.05	2	-1	1.8	-2.0	-0.1
0.2	0.1	2	-1	2.1	-2.4	-0.1
0.2	0.2	2	-1	-2.7	0.9	-1.3
0.2	0.3	2	-1	-2.7	0.6	-1.4
0.2	0.4	2	-1	-3.8	28	23.6

*N=2000, R=1000. Note that the difference in true WTP and estimated WTP was calculated based on the median of true WTP and the median of parameter estimates in the joint RP-SP models which mutes the underlying variation that would be seen if I calculate WTP for each of the 2000 people for the 1000 runs (authors can provide this if desired).

2.5. Conclusion

Ecosystem services generally provide both use and non-use economic values. We began by noting an existing discrepancy among the valuation methods to measure non-use values, especially for environmental resources. We highlighted a structural estimation framework that allows decomposition of use and non-use values. WTP estimates from this model provide specific information to policy makers and federal agencies, by linking the change of ecosystem services to individual WTPs for use and non-use. Information on ratios of use and non-use values for different ecosystem services is often critical when time pressures or budgets restrict the available information for decision making in the extant literature.

We use data generated experiments to demonstrate that the proposed structural model generally, but not always, provides consistent results in estimating true values of parameters of interest and recovering true WTPs, which can be applied to a wide range of valuation studies. This Monte Carlo study indicates that the structural model estimates of use and non-use values have the lowest bias when the marginal utility of use and non-use quality are at a comparable level, and the performance in situations where the relative use and non-use value are more divergent is poor for some parameters of interest. We recognize that the structural model can be sensitive to research design (e.g., the variation in environmental quality within a RP or SP data), while the conceptual framework can be applied to any setting involving pooling different types of choice data (i.e., portfolio choices and general purchase decisions) or requiring testing of estimator properties with complex empirical data. Since having rich revealed preference data and appropriate stated preference data enables and helps to quantify use and non-use WTP at the same time, the results show attention should be paid to these in the data collection and survey design of studies implementing the approach.

Future work should focus on addressing two concerns: (1) choice of the type of stated preference data and (2) revealed preference model specification. As many previous works find a trade-off between incentive compatibility and the number of choices, some research designs will work well with this type of model, but others do not. In cases where there is limited variation in stated choices (i.e., in a consequential single referendum choice per person), the results may provide biased value estimates. Second, future research would assist with understanding whether and to what extent use and non-use values would be impacted by other reveled preference model specifications (i.e., single site demand model, Kuhn-Tucker model, or count models).

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APPENDIX

Table 2A.1: Median and Confidence Intervals of Parameter Estimates in the Joint RP-SP Logit Model (when λ is fixed at -1)

True β	True b	True	Median Use Quality $\hat{\beta}$	Median Non-use Quality $\hat{b}$	Median Scaling Factor $\hat{\sigma}$
0.2	0.05	2	0.2086 [0.1873,0.2318]	0.0328 [-0.0138,0.0717]	2.1099 [2.0056,2.2218]
0.2	0.1	2	0.2101 [0.1895,0.2332]	0.0791 [0.0335, 0.1200]	2.0231 [1.9238, 2.1390]
0.2	0.2	2	0.1845 [0.1621, 0.2105]	0.0898 [0.0363, 0.2010]	1.8579 [1.7242, 1.9908]
0.2	0.3	2	0.1712 [0.1445, 0.2005]	0.1957 [0.1064, 0.3073]	1.8516 [1.6938, 2.0196]
0.2	0.4	2	0.1685 [0.1326, 0.2020]	0.3975 [0.1926, 0.5972]	1.8934 [1.6979, 2.1245]

* All runs with sample set at N=2,000 using R=1,000 replications with 90% confidence intervals in brackets
* True γ is -0.02 for all cases and well estimated throughout different parameter specification.
* True λ is -1 for all cases.
* A full set of site alternative specific constants (ASCs) for 38 sites were included in the joint RP-SP logit model.

Table 2A.2: Bias of Structural Estimators (when λ is fixed at -1)

True β	True b	True σ	Bias ($\hat{\beta}$)	Bias ($\hat{b}$)	Bias ($\hat{\sigma}$)
0.2	0.05	2	0.01	-0.02	0.11
0.2	0.1	2	0.01	-0.02	0.02
0.2	0.2	2	-0.02	-0.11	-0.14
0.2	0.3	2	-0.03	-0.10	-0.15
0.2	0.4	2	-0.03	0.00	-0.11

Table 2A.3: Median and Confidence Intervals of Parameter Estimates in the Joint RP-SP Logit Model (when λ is estimated and equal to -1)

True β	True b	True σ	Median Use Quality $\hat{\beta}$	Median Non-use Quality $\hat{b}$	Median Scaling Factor $\hat{\sigma}$	Distance Decay $\hat{\lambda}$
0.2	0.05	2	0.1866 [0.1623, 0.2275]	0.0058 [-0.2182, 0.0508]	2.0553 [1.9320, 2.1751]	-0.5281 [-0.4654, 0.1706]
0.2	0.1	2	0.1909 [0.1694, 0.2253]	0.0259 [0.0016, 0.1001]	1.9647 [1.8480, 2.0866]	-0.6470 [-0.9882, -0.7268]
0.2	0.2	2	0.1845 [0.1620, 0.2105]	0.0899 [0.0361, 0.2010]	1.8579 [1.7348, 1.9906]	-0.7968 [-0.9530, -0.4572]
0.2	0.3	2	0.1713 [0.1444, 0.2005]	0.1956 [0.1063, 0.3073]	1.8524 [1.6936, 2.0196]	-0.8736 [-0.9775, -0.8903]
0.2	0.4	2	0.1685 [0.1326, 0.2020]	0.3975 [0.1928, 0.5975]	1.8935 [1.6979, 2.1250]	-0.9585 [-1.0939, -0.8677]

* All runs with sample set at N=2,000 using R=1,000 replications with 90% confidence intervals in brackets
* True γ is -0.02 for all cases and well estimated throughout different parameter specification.
* True λ is -1 for all cases.

Table 2A.4: Bias of Structural Estimators (when λ is estimated and equal to -1)

True β	True b	True σ	Bias ($\hat{\beta}$)	Bias ($\hat{b}$)	Bias ($\hat{\sigma}$)	Bias ($\hat{\lambda}$)
0.2	0.05	2	-0.01	-0.04	0.06	0.47
0.2	0.1	2	-0.01	-0.07	-0.04	0.36
0.2	0.2	2	-0.02	-0.11	-0.14	0.20
0.2	0.3	2	-0.03	-0.10	-0.15	0.13
0.2	0.4	2	-0.03	0.00	-0.11	0.04

Table 2A.5: Median Use, Non-use, and Total WTP Estimates and
Median Ratio of Non-use WTP to Total WTP ($'s) (when λ is fixed at -1)

True β	True b	True σ	True λ	Median Use WTP ($)	Median Non-use WTP ($)	Median Total WTP ($)	Median Ratio (Non-use /Total)
				29.7	5.9	35.5	
0.2	0.05	2	-1	[0.0, 49.6]	[0.9, 14.2]	[1.1, 57.8]	0.17
				(10.8, 40.5)	(3.6, 8.8)	(15.7, 48.3)	
				29.7	11.8	41.4	0.28
0.2	0.1	2	-1	[0.0, 49.6]	[1.8, 28.5]	[2.2, 72.0]	
				(10.8, 40.5)	(7.3, 17.6)	(20.2, 56.2)	
				29.7	23.7	53.2	0.44
0.2	0.2	2	-1	[0.0, 49.6]	[3.7, 57.0]	[4.1, 101.3]	
				(10.8, 40.5)	(14.6, 28.8)	(28.8, 72.9)	
				29.7	35.5	65.0	0.55
0.2	0.3	2	-1	[0.0, 49.6]	[5.5, 85.4]	[5.9, 130.6]	
				(10.8, 40.5)	(21.8, 52.7)	(36.7, 89.9)	
				29.7	47.3	77.7	0.61
0.2	0.4	2	-1	[0.0, 49.6]	[7.3, 113.9]	[7.4, 159.9]	
				(10.8, 40.5)	(29.1, 70.2)	(45.8, 107.5)	

*N=2000, R=1000. Minimum and maximum values of WTP are reported in the square bracket to capture the variability among the simulated people since each person in the simulation had a random draw of the change in quality. 90% confidence interval in the round bracket. Also note that the WTP estimates were calculated based on true values of parameters in the joint RP-SP models.

Table 2A.6: Median Use, Non-use, and Total WTP Estimates and
Median Ratio of Non-use WTP to Total WTP ($'s) (when λ is estimated and equal to -1)

True β	True b	True σ	True λ	Median Use WTP ($)	Median Non-use WTP ($)	Median Total WTP ($)	Median Ratio (Non-use /Total)
				31.5	3.9	35.4	
0.2	0.05	2	-1	[0.0, 53.3]	[0.6, 9.7]	[1.1, 57.8]	0.11
				(11.8, 43.2)	(2.4, 5.7)	(15.7, 48.3)	
				31.8	9.4	41.2	0.23
0.2	0.1	2	-1	[0.0, 53.8]	[1.4, 23.5]	[1.8, 69.2]	
				(31.8, 43.7)	(5.7, 13.9)	(19.3, 56.1)	
				27.0	24.6	51.9	0.47
0.2	0.2	2	-1	[0.0, 46.6]	[3.6, 61.4]	[4.0, 97.8]	
				(10.0, 37.4)	(14.9, 36.3)	(29.0, 70.6)	
				27.0	36.1	63.6	0.57
0.2	0.3	2	-1	[0.0, 46.6]	[5.3, 90.2]	[5.7, 126.1]	
				(10.0, 37.4)	(21.8, 53.2)	(37.8, 87.3)	
				25.88	75.3	101.3	0.74
0.2	0.4	2	-1	[0.0, 44.8]	[11.0, 188.2]	[11.5, 219.3]	
				(9.6, 35.9)	(45.6, 111.1)	(64.0, 141.4)	

*N=2000, R=1000. Minimum and maximum values of WTP are reported in the square bracket to capture the variability among the simulated people since each person in the simulation had a random draw of the change in quality. 90% confidence interval in the round bracket. Note that the WTP estimates were calculated based on median values of parameter estimates in the joint RP-SP models, which mutes the underlying variation that would be seen if I calculate WTP for each of the 2000 people for the 1000 runs (authors can provide this if desired).

Essay 3: Comparing Structural Estimation of Use and Non-use Values for Water Quality to Simpler Ad hoc Approaches

3.1. Introduction

Federal, state, and local agencies tasked with protecting the nation's water resources must balance costs and benefits of proposed regulatory programs (e.g., U.S. Environmental Protection Agency (EPA) is subject to presidential executive orders that require benefit-cost analysis for all substantive programs). While program cost calculations can be challenging, the more difficult task is often quantifying and assessing the benefits of environmental improvements. The benefits of water quality improvements include both the use and non-use values held by individuals. Disentangling the use and non-use values remains an area of ongoing research, which is important since many EPA analyses must rely on benefits transfer from existing literature that uses a mix of revealed preference (RP) and stated preference (SP) approaches (Griffiths et al., 2012).

A variety of techniques have been employed in literature to distinguish use and non-use values. Johnston, Besedin and Wardwell (2003) identify five approaches in the SP literature: (1) non-use values identified as the total willingness-to-pay (WTP) for non-users; (2) responses to separate non-use value questions in the survey; (3) apportionment of total WTP among categories of value by survey respondents; (4) non-use values estimated as the total WTP of a survey sample who were asked to assume they would not use the resource being valued; and (5) total WTP of the sample of users minus estimated WTP for the direct use of the resource estimated based on revealed preference data." Each of these has its respective shortcomings. An alternative approach is to simultaneously model the valuations of users and non-users in an integrated framework, employed in Eom and Larson (2006), Egan (2011), Day et al. (2019), and Landry, Shonkwiler and Whitehead (2020). However, these ``structural" models are complex and unlikely to see widespread application. What is needed is a comparison of the resulting use and non-use valuations for both the complex modeling approach and the simpler methods currently employed in the literature to better inform use of existing studies in benefits transfers and policy analyses.

This paper explores the joint estimation of revealed and stated preference recreation demand model to separately identify use and non-use values. Building on the existing literature, I apply the structurally consistent estimation method that Day et al. (2019) developed for random utility models to a setting where each person answers a single referendum contingent valuation question and reports a full panel of water-based recreation trips for a season. In addition, I extend the Day et al. (2019) recreation portion to a nested logit repeated random utility model (RUM) for season trips rather than a conditional logit. I also extend the Day et al. (2019) work by using a full set of site-specific fixed effects in the empirical model. Using rich survey data collected in Spring 2020, I compare the result of this structural method for measuring use and non-use values to results of *ad hoc* estimation methods mentioned in Johnston et al. (2003). A key contribution of this study is that the same survey was used to collect the data for the structural decomposition of use and non-use values and the data for several of the *ad hoc* ways of doing so mentioned in Johnston et al. (2003), thereby providing a consistent comparison for each approach.

I study this problem in the context of changing water quality in Michigan waterbodies, an issue relevant to analyses of federal regulations under the Clean Water Act and other water quality rulemaking. Unlike many studies in this literature, the survey data (1) was not limited to users (Egan, 2011; Eom & Larson, 2006), (2) did not rely on non-probability panels (Landry et al., 2020), (3) was representative of a broad region (Day et al., 2019), and (4) covered all water-based recreation rather than a specific type of use (e.g., fishing). The carefully designed general population survey used random sampling of United States Postal Service (USPS) known postal addresses to help assure the data represents the overall population. The sample was sent a letter with a website address (i.e., a ``push-to-web" approach) and achieved over 2,300 responses (a 23% response rate). The survey invitations used phrases such public policy issues to avoid sample selection bias due to interest or participation in water-related recreation. Before the Michigan general population survey was implemented, I conducted qualitative interviews to test and evaluate the instruments, conducted a large pilot survey in 2019, made further revisions to the survey with an additional round of interviews, and followed the suggestions for best practices by Johnston et al. (2017) and Lupi, Phaneuf and von Haefen (2020). These efforts help establish internal validity of the study.

Preliminary results from the RP-only and SP-only separate analyses show significant positive values for changes in water quality, and both show the expected sensitivity to the scope of water quality changes. In SP-only analyses, people who use waterbodies for recreational purposes show higher marginal willingness to pay (MWTP) for improved water quality than non-users. The magnitude of MWTP differs across four types of water quality indices, which represent different biological conditions.

In the previous essay, I examined the estimation and identification strategy for our structural model with a full set of site fixed effects which shows the identification of key parameters of interest. In this essay, I apply the structural model to our empirical data, and with the results, I will compare the estimates of use and non-use values to those implied by the *ad hoc* approaches and relate these back to mixed results in the existing literature. For example, some other studies on water quality issues find that use value is greater than non-use value in total value estimated using the RP-SP models (Egan, 2011; Eom & Larson, 2006), whereas Day et al. (2019)'s structural estimation finds that welfare measures from non-use utility are greater than those from use utility. However, the empirical model encounters convergence issues when there is a little variability in SP data. Thus, it is not promising to use this complicated method of the structural modeling approach to measure use and non-use values considering difficulty and time.

3.2. Literature and Background

Non-market valuation is a tool for economic valuation of ecosystem services, based on a link between changes in the quantity or quality of the resource and the changes in the stated or observed behavior of people. The measurement of this relationship facilitates the comparison of values of non-market goods in monetary units. For example, contingent valuation studies have been used to assess the damages to waterbodies caused by accidents such as oil spills and inform administrative and judicial decisions (Bishop et al., 2017; Carson et al., 2003; English et al., 2018; Loomis, 1997). Use and existence values of water quality changes can be measured in a hypothetical market, consistent with economic theory, and they can be used as a starting point for resource management decision of government agencies (Carson, 2012; Kling et al., 2012).

Of the myriad benefits that the natural environment provides, some of the values are relatively straightforward to measure through revealed market transactions (Arrow et al., 1993). For example, use values are reflected in observed behavior of individuals who actively use water resources (recreational fishers, boaters, swimmers, hikers, and others). Individuals use environmental amenities to enhance their welfare by producing utility yielding goods or services, or by using them as substitutes for, or complements to, market goods such as recreation trips (Freeman, Herriges and Kling 2014). Non-use values, however, are independent of a person's present or future use of the resource. Broadly defined, non-users are individuals who do not use a particular site but may derive utility from its existence or for others' use. Although alternative views exist on the definition of, classification of, and boundary between use and non-use values, Smith (1987) conceptualizes non-use benefits as existence value and option value.

A key challenge that arises in estimating the benefits is to conceptualize non-use values and distinguish them from use values; use and non-use values combined result in the total economic value of resources. This is especially important for meta-analyses of values seeking to isolate the value types and for filling in gaps in literature in other areas where it becomes useful to draw upon ratios of use and non-use found in the literature (Griffiths et al., 2012). Yet, at times a fuzzy definition of use and non-use values prevails in literature and makes it difficult to select a legitimate empirical model to determine non-use values. Johnston et al. (2003) survey various methods to measure non-use value.

A common ad hoc approach to define use and non-use is to treat use values as the value held by users and non-use values as the values held by non-users and compare total willingness to pay (WTP) for non-users with total WTP for users. For example, Croke, Fabian and Brenninam (1987) classify survey respondents who currently use rivers as users and find that the mean willingness to pay for water quality improvements is higher among users than non-users. Whitehead et al. (1995) find the WTP of on-site users are greater than WTP of off-site users or WTP of non-users when comparing WTP of three groups (on-site users, off-site users, and non-users). Similarly, Bockstael, McConnell and Strand (1989)'s contingent valuation survey results show that users are more willing to pay a tax for water quality improvements in the Chesapeake Bay, with the sample comprised of 43% users and 57% non-users. Whittington et al. (1994)

also find that a typical user of Galveston Bay is more likely to support the plan for environmental quality improvement than a typical non-user. A shortcoming of this approach is that it could imply users do not have non-use values. Even the definition of "users" differs across studies. Some papers define users as visitors and non-users as non-visitors. Similarly, users may have non-use values for other alternatives that they do not use. Non-users in a specific time period may hold use values for any resource at different places and times.

Another method that has been used in previous literature is to compare the WTP bids for different purposes: use purposes and non-use purposes. Lant and Roberts (1990) let the WTP for recreational use represent use values and the WTP for intrinsic values be non-use values. They find that non-use value benefits of river quality improvement exceed the benefits for direct use. Other studies rely on the respondent's decomposition of values into categories of use and non-use values Roberts and Leitch (1997). For example, after respondents report their total, a follow up question would ask them to apportion the total WTP into use, option, and existence values categories (Kaoru, 1993; Sanders et al., 1990; Sutherland & Walsh, 1985).

A few examples venture to estimate non-use values as the total WTP of a survey sample who were asked to assume they would not use the resource being valued. Magat et al. (2000) examine the rate of tradeoff between water quality improvements in the person's own region versus water quality improvements in a region that the respondent will not visit. They also analyze the potential values of water quality based on the probability that the respondent will visit another region. This type of research design attempts to take non-use and probabilistic use values into account.

More recently, researchers have devised more delicate survey designs and estimation strategies as methods evolve. Under a combined revealed and stated preference setting, the models estimate non-use values as total WTP of the sample of users minus estimated WTP for the direct use of the resource estimated based on revealed preference data (Eom and Larson 2006; Whitehead et al. 2008; Egan 2011). Landry et al. (2020) estimate models of beach recreation demand and total WTP. They find evidence of significant welfare gains from beach erosion control policies that affect beach width and coastal environmental quality with a large component for existence values.

In this project, I collect both RP and SP data for use and non-use value estimation, followed by additional responses for use and non-use split and an alternative contingent valuation elicitation format. I exploit both simpler and complicated models using a series of consistently measured data all from the same survey. Assuming that trip takers are users, I can divide respondents into the group of users and non-users and use SP models to compare total willingness to pay of the user group and that of the non-user group. The contingent valuation question is in the format of a single dichotomous and consequential policy referendum, followed by an open-ended comment box. Though the survey does not require respondents to divide their WTP into fuzzy groups of non-use values, it includes questions directly asking the percentage of use and non-use values that respondents would derive from the water quality changes. Data from questions on recreational use (RP information) and referendum data (SP information) for proposed policy scenarios that change water quality indices of waterbodies are used in structural estimation.

3.3. Theoretical Motivation for Use and Non-use Utility Model

3.3.1. Structural Model of Use and Non-use Utility

I build on the structurally consistent model of Day et al. (2019), incorporating both revealed preference and stated preference data in the demand for improved water quality to identify use and non-use values. I extend their empirical framework to include a full set of site fixed effects (also called alternative specific constants) following the advice of Murdock (2006) and Lupi et al. (2020) since the fixed effects can control for any omitted variable bias for site quality. By combining the revealed preference data on site choices under baseline water quality with stated preference referendum data under quality changes, I can identify the effect of quality changes separate from the site fixed effects.

Let a sample of individuals ($i = 1, \dots, \mathrm{N}$) maximize their indirect utility by choosing recreation sites among waterbodies ($j = 1, \dots., \mathrm{J}$) and vote for or against a hypothetical scenario on environmental quality change. Our theoretical framework does not preclude users from holding non-use values. Thus, it is assumed that individuals gain utility from three separable components: utility from using a site for outdoor recreation, utility from waterbodies without having to use any complementary market goods, and utility from consuming a composite good z_i.

$$U(U^{Use}(\boldsymbol{x_{is}}, q_{1s}, \dots, q_{Js}), U^{NonUse}(q_{1s}, \dots, q_{Js}, \boldsymbol{d_i}), z_i) \qquad (1)$$

Let individuals' utility from recreational trips be $U^{Use}(\boldsymbol{x_{is}}, q_{1s}, \dots, q_{Js})$ where q_{js} measures the water quality at site *j*. Both use and non-use utility depend on qualities of sites q_{js}. Qualities q_{js} differ across the J sites, and possible scenarios of water quality (*s* = 0, 1, …, S), where s = 0 is the baseline water quality level and alternative water quality scenario is denoted by s = 1, …, S. Non-use utility derived from a site is a function of site qualities and distance from one's home to each site $\boldsymbol{d_i} = (d_{i1}, \dots, d_{iJ})$. Finally, z_i is a numeraire good that individual *i* consumes with price 1.

Individuals maximize their utility by making a recreational use decision among sites with varying quality. The decision is characterized by a vector of consumption levels of trips $\boldsymbol{x_{is}} = (x_{i1s}, x_{i2s}, \dots, x_{iJs})$ and a travel cost vector $\boldsymbol{p_i} = (p_{i1}, p_{i2}, \dots, p_{iJ})$, which captures the travel cost and the opportunity cost of travel time. Subject to their budget constraint, they choose how frequently to visit a recreational site *j* with quality q_{js} for their recreation activities and how much they consume for a composite good. For each choice occasion *t*, an individual faces the following maximization problem:

$$\max_{x_{its},\ z_{its}} U(U^{Use}(x_{its}, q_{1s}, \dots, q_{Js}), U^{NonUse}(q_{1s}, \dots, q_{Js}, \boldsymbol{d_i}), z_{its}) \qquad (2)$$

$$s.t. \quad y_{it} = \boldsymbol{p_i'} x_{its} + z_i$$

$$x_{jts} \in \{0, 1\}$$

$$x_{jts} x_{kts} = 0 \ (\forall k \neq j)$$

To solve this discrete choice problem, I impose three assumptions. First, the utility is increasing in all three arguments, i.e., the more individuals perceive utility from recreation trips, the more they gain utility from sites they are not using, and the more they spend on a composite good, the happier they are. Second, the use utility follows weak complementarity (WC). When individuals do not visit a site *j* at a choice occasion *t*, the use utility that the person derives from the quality of the site is zero. Third, preferences are strongly separable over time. In the context of recreation demand models, time *t* indicates recreational choice periods of equal length $t = 1, 2, \ldots, T$. Typically, the number of weeks during a study period is chosen to be the total number of choice occasions T.

When individual i chooses to visit site j on a choice occasion t, $x_{jts} = 1$ and $x_{jts}x_{kts} = 0$ $(\forall k \neq j)$, the budget constraint binds $z_i = y_{it} - \boldsymbol{p}_i' x_{its} = y_{it} - p_{ij}$. The indirect utility of individual i conditional on visiting site j is then

$$u_{its|j} = u\left(u^{Use}\left(q_{\boldsymbol{js}}\right), u^{NonUse}\left(q_{1s}, \ldots, q_{Js}, \boldsymbol{d_i}\right), y_{it} - p_{ij}\right) \qquad \forall\, i, t, s \tag{3}$$

Individuals derive non-use utility from the qualities of all the sites. However, they derive use utility only from a site j where $x_{jts} \neq 0$. The model of recreation behavior follows the rational choice rule:

$$\text{Choose to visit site } j \text{ in period } t \text{ if} \qquad u_{its|j} > \left\{u_{its|k}\right\}_{\forall\, k \neq j} \;\; \forall\, i, t, s \tag{4}$$

In each choice occasion, individuals decide their recreational choice for each site. They visit site j when the conditional indirect utility from visiting site j is larger than that from visiting sites other than j.

Then, they decide whether to vote for or against a hypothetical scenario on water quality change from a discrete set of potential scenarios. In a contingent valuation question, one random hypothetical scenario s with water quality changes (q_{j0} to q_{js}) and necessary lump-sum payment ($C_s = T \times c_s$) is presented to each respondent. Per choice occasion policy cost is defined as c_s. They are asked to vote for or vote against the scenario. When accounting for the one-time payment from the referendum on individuals' income tax for a water quality improvement policy in the net income, the conditional indirect utility function becomes

$$u_{its|j} = u\left(u^{Use}\left(q_{js}\right), u^{NonUse}\left(q_{1s}, \ldots, q_{Js}, \boldsymbol{d_i}\right), y_{it} - p_{ij} - c_s\right) \qquad \forall\, i, t, s \tag{5}$$

and the rational choice rule follows:

$$\text{Vote yes to pay } C_s \text{ if} \qquad \sum_{t=1}^{T} \max_j \left(u_{its|j}\right) > \sum_{t=1}^{T} \max_j u_{it0|j} \quad s \in S \tag{6}$$

Individuals decide whether to not to choose a hypothetical scenario s if the expected indirect utility from scenario s is greater than the indirect utility from a baseline environmental condition $s = 0$, an individual maximizes its utility for recreational trips and market goods conditional on its income after the per period payment for improved environmental quality c_s, where c_s is a hypothetical lump-sum payment divided by the number of choice occasions for the study period. Note that the model assumes that consumers can perceive the change of water quality q_{js} and that the utility function is inter-temporally additively separable.

3.3.2. Alternative Approaches for Use and Non-use Utility

Contrary to the structural model of use and non-use utility pooled using both RP and SP data, simpler *ad hoc* models are often based on stated preference data only. Here, I use our structural model to interpret two widely used *ad-hoc* approaches.

3.3.2.1. User vs. Non-users Framework

This conceptual framework is based on survey respondents to a stated preference survey. At the extreme, use values are defined as the total willingness to pay values held by users, and non-use values are defined as the values held by non-users. No assumption is necessarily made on distance decay. But with the dichotomous definition of users and non-users, it is assumed that users do not hold any non-use utility. Users draw their utility for the change in quality only from the use of a specific site *j* at each choice occasion *t* (use utility). Likewise, it is assumed that non-users do not hold any use utility for the change in quality.

$$u_{its|j}^{user} = u\left(u^{Use}\left(\Delta q_j\right), 0, y_{it} - p_{ij} - c_s\right) \tag{7}$$

$$u_{its|j}^{nonuser} = u\left(0, u^{NonUse}\left(\Delta q_j\right), y_{it} - p_{ij} - c_s\right) \tag{8}$$

The maximum utility of each user is

$$U^{user} = \sum_{t=1}^{T} \max_j u_{its|j}^{user}, \qquad s \in S \tag{9}$$

The maximum utility of each non-user follows

$$U^{nonuser} = \sum_{t=1}^{T} \max_j u_{its|j}^{nonuser}, \qquad s \in S \tag{10}$$

3.3.2.2. Direct Apportionment of Use and Non-use Values

Another common type of application relies on direct apportionment of use and non-use values by individuals. Following a contingent valuation question respondents are asked to report the fraction of their total WTP for use and non-use purposes. In this setting, individuals decide what percentage of the value they place on use values and non-use values. For instance, if they consider that their total willingness to pay (WTP) for an improvement in water quality is (100·X)% for use values, then (100·(1-X))% is attributed to non-use values. The combined percentage of the value from use values and non-use values always adds up to 100%, meaning that X and 1-X must equal 1.

The conditional indirect utility function from equation 5 will be subdivided into two separate utility functions as below:

$$u^{Use} = X \cdot \; u\big(u^{Use}(q_{js}), u^{NonUse}(q_{1s}, \dots, q_{Js}, \boldsymbol{d_i}), y_{it} - p_{ij} - c_s\big) \quad (11)$$

$$u^{NonUse} = (1 - X) \cdot \; u\big(u^{Use}(q_{js}), u^{NonUse}(q_{1s}, \dots, q_{Js}, \boldsymbol{d_i}), y_{it} - p_{ij} - c_s\big) \quad (12)$$

3.4. Data Sources and Study Sample

The structural identification of use and non-use values for environmental quality change requires two types of data sets: a set of revealed preference (RP) data of recreational use and a set of stated preference (SP) data. In this paper, contingent valuation referendum data are elicited via survey instruments. A general population push-to-web survey was used for collecting detailed recreational use behavior as well as responses to a single dichotomous and consequential referendum question per person. This section describes how the survey was designed, how data collection was planned and implemented, and how data were processed.

3.4.1. Michigan General Population Survey

Study participants were drawn from an address-based random sample of 12,000 residents of Michigan's lower peninsula. The address list was purchased from a licensed vendor of the US Postal Services delivery sequence file for all occupied residential addresses in Michigan. For policy relevance, general population sampling has advantages over nonrepresentative approaches such as convenience samples or online consumer panels (Lupi et al. 2020). The list was stratified by county so that addresses were proportional to adult populations.

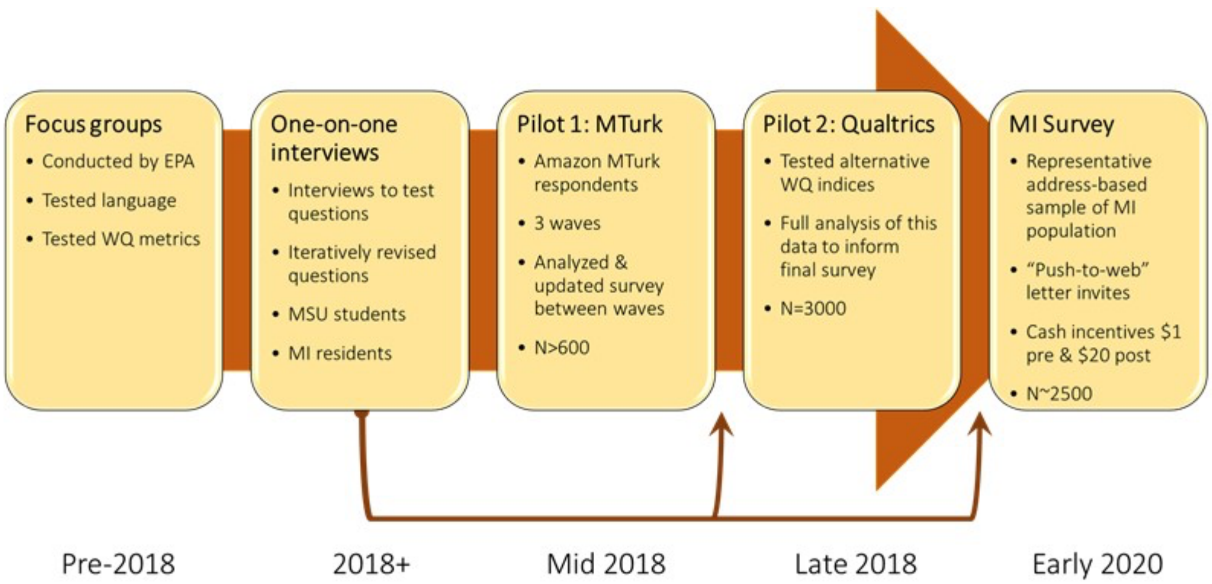
The survey ran from February to April 2020. In the first contact, a letter invitation was mailed to each address with an up-front $1 incentive. The letter encouraged sample respondents to visit a designated web page online and complete a web-based survey, using a passcode customized to each individual. Postcard reminders were sent out to those who had not yet responded. Continued non-respondents were then sent a second reminder letter that also offered a $20 completion incentive. The last contact consisted of a final reminder postcard that again mentioned the completion incentive. Respondents were given an option to be paid $20 or to donate the money back to the project and about 37% donated back to the project. To avoid sample selection effects that would bias water users to respond to the survey (Lupi et al. 2020; Johnston et al. 2017), the invitation materials and first section of the survey said almost nothing about water quality and recreation. About 22.5% of the address-based sample logged into the survey and completed the first survey section asking about household decision-making and attitudes toward public policy issues in Michigan.[3]

The survey questions and Information treatments were carefully designed following best practices for revealed and stated preference studies (Lupi et al. 2020; Johnston et al. 2017). The survey development steps and timing are outlined in Figure 3.1. Before launching the 2020 Michigan general population survey, thorough survey pretesting was implemented to improve the accuracy and quality of survey design, and hence to increase the validity and reliability of the valuation result. Survey pretesting procedures included cognitive interviews and pilot surveys using online panel respondents. Specifically, in early 2018, the survey instruments were developed and leveraged extensive designs and focus group interviews that were conducted by US Environmental Protection Agency (EPA) to test possible water quality metrics and survey language (Moore et al, personal correspondence).[4] Then, one-on-one cognitive interviews were conducted with Michigan State University students and with members of the general population recruited through the Amazon mTurk platform. Throughout the qualitative work, the questions and information treatments were

[3] After the introductory screening and policy attitudes section, the survey elicits water recreation and then contains the contingent valuation portion. Almost all respondents that completed the first section continued with all or most of the survey: about 97% provided recreation data and 86% completed to the end of the survey.
[4] The EPA team shared all focus group materials and notes for their seven focus groups, but their summary paper with findings is not yet approved for publication.

iteratively revised (Kaplowitz et al. 2014). In mid-2018, I launched a pre-test survey on mTurk to further test the questions with actual data and collect responses for an experimental design. Following analyses and review of these approximately 600 responses (Pilot 1), I made revisions in experimental design and launched a 3,000-person pilot survey using Qualtrics' on-line panel of respondents (Pilot 2). To inform the final Michigan general population survey, I conducted analysis of this data.[5] Finally, based on the pilot, I made further revisions and again tested them using one-on-one cognitive interviews with MSU students and Michigan residents recruited from mTurk.

Figure 3.1: Survey Development Timeline and Key Steps



[5] Johnston et al (2017) suggest SP studies summarize some key revisions made to instruments during testing, so here are a few items. From our pilot survey, I learned that acquiring precise trip locations is important to characterize the revealed use behavior of individuals, so I updated the revealed preference section to have a table-type question on a full inventory of trip locations (waterbody names and nearest cities). For the stated preference section, based on pilot modeling results testing multiple indices, I chose to use four water quality indices that reflect various aspects of ecosystem services related to water quality. To inform respondents well and make sure policy scenarios are interpreted as intended, I supplemented the survey with additional information about the overall distribution of water quality rather than simply the statewide means of water quality metrics. Also, I added questions after the referendum on splitting use and non-use value components to study empirical use and non-use models based on respondents' evaluation.

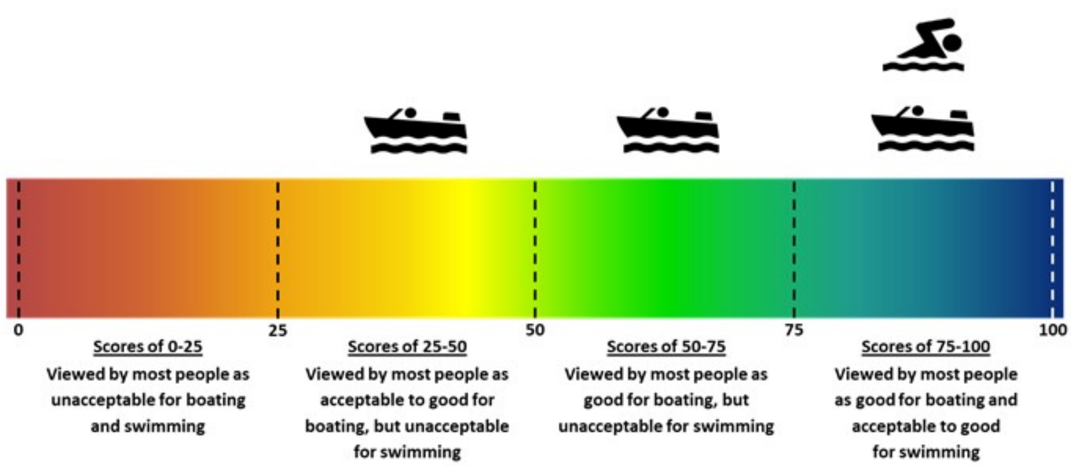
3.4.2. Water Quality Indices and Data

In the survey, respondents were presented "scores" for water quality that focus on four categories defined as follows:

- Water Clarity – The clarity of waterbodies (how far one can see through the water)
- Water Contact – The suitability of waterbodies for contact such as wading and swimming
- Fishing Water Quality – The suitability of waterbodies for recreational fishing
- Wildlife Water Quality – The ability of waterbodies to support healthy and diverse populations of naturally occurring aquatic plants and animals.

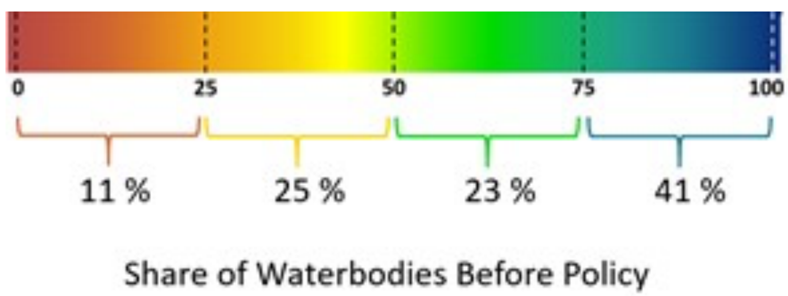
The survey explicitly explains to the respondents that it is about the ways that water quality affects these four separate water quality scores. A water quality score is a way to express the effects of important water quality characteristics (such as water clarity, bacteria levels, fishing quality and aquatic wildlife quality). All the water quality scores used in this survey are continuous and range from 0 (worst possible quality) to 100 (best possible quality). Each score was explained with text and illustrated graphically using a color bar that was accompanied by text descriptions for different levels in a manner that builds upon existing water quality indices and ladders used by EPA (see Figure 3.2). From now on, I will use the abbreviation for each water quality index as follows: Water Clarity Score (CLS), Water Contact Score (WCS), Fishing and Biomass Score (FBS), and Wildlife Score (WLS).

Figure 3.2: Example scale and levels of water quality for the Water Contact Score (WCS)



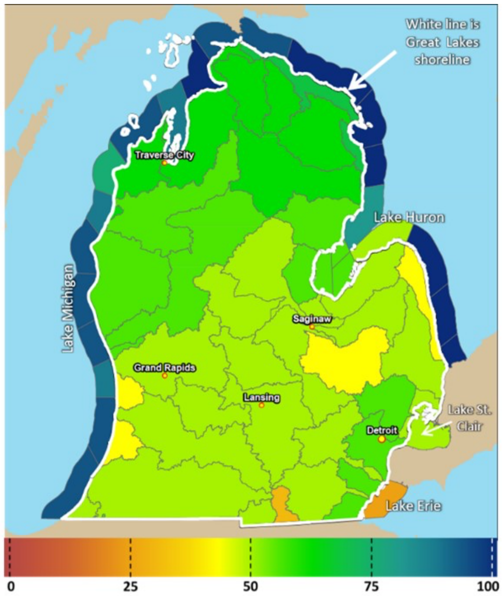
The baseline values of water quality scores were constructed for each HUC8 zone (j = 1, …, 64) in the lower peninsula of Michigan. HUCs contain various types of waterbodies (either Great Lakes or inland lakes, rivers and streams). Each of the water quality scores were developed by a team of MSU researchers including an ecologist, and the scores are based on data and ecological models for Michigan. For each water quality index, respondents were presented with three types of summary statistics: (1) the average value of the water quality score in Michigan's lower peninsula (LP), (2) a map of the average value of water quality within each HUC8 (Figure 3.4), and (3) a graphic depicting the distribution of water quality across the LP (Figure 3.3).

Figure 3.3: The share of all waterbodies in each range of water quality scores (Example of WCS)

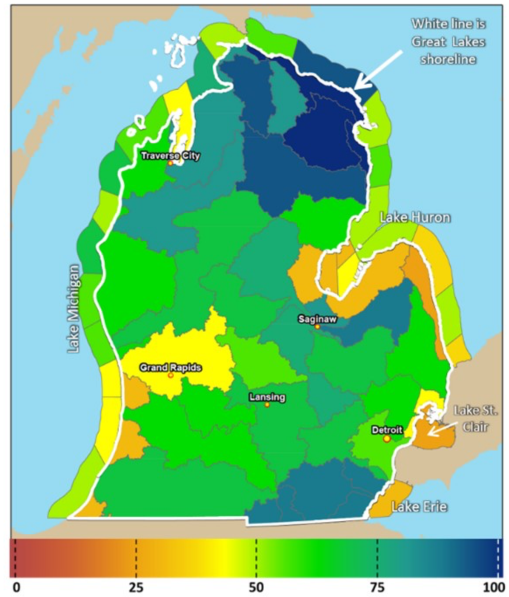


The color value in the map in Figure 3.4 represents the average value of water quality within each HUC8 in the baseline without any policy change. In the stated preference question, all the three types of information on water quality indices were provided to respondents, along with how each score would change with the policy scenario. To avoid any ordering effects, I randomize the order that four water quality indices are introduced and displayed in the questions and tables.

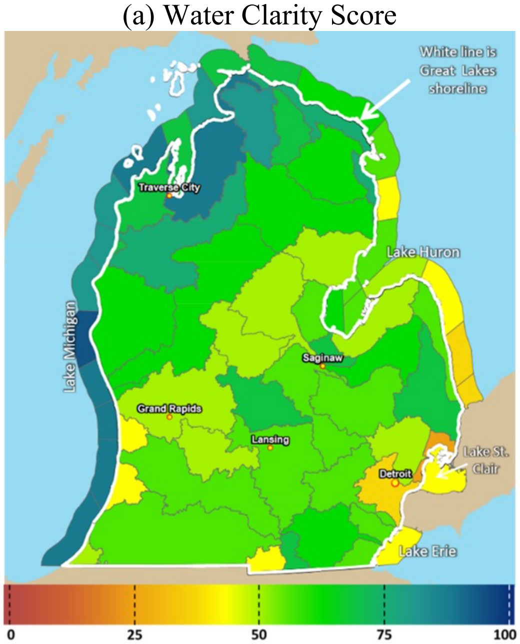
Figure 3.4: Baseline Map of Four Water Quality Scores



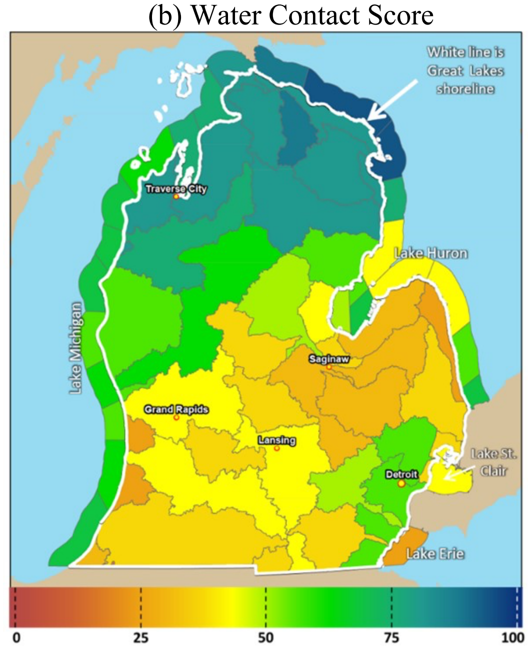
(a) Water Clarity Score



(b) Water Contact Score



(c) Fishing Quality Score



(d) Wildlife Water Quality Score

3.4.3. Recreational Use Data from Trip Elicitation Questions

For the recreation demand model, I use the survey data to identify the number of trips and the location of each trip. Each respondent was asked to report whether in the last two years they have gone to a waterbody in Michigan for the main purpose of water-based recreation. If they indicate they went, as did 75% of survey respondents, I then ask a question about types of water-based recreation to reinforce the definition of activities, and they are asked whether they went to a waterbody in Michigan from June through August 2019 for the primary purpose of water-based recreation. For the 70% of respondents who said yes, they were asked to report details about each site visited (the number of trips, the name of the waterbody that they went to, and the nearest town or city to the waterbody) for up to five most frequently visited recreation sites. To aid in recall, respondents were shown a calendar for the reporting periods, and to facilitate accuracy and reporting of trip locations, I implemented an auto-fill function using lists of site and city names for the text entry fields. For any additional sites besides the five most visited sites, the total number of trips to these other sites is collected. For people that reported trips to more than one site, the numbers they reported were summarized and shown to them in a table with the totals, and they were given an opportunity to verify them and adjust them if desired.

To capture individual characteristics that could affect travel cost, I collected the following information on the vehicle typically used for their trips: the type of vehicle, the number of people that traveled in the same vehicle, and an indicator for whether they towed a trailer or boat. In specifying the cost of travel, I follow previous literature and practices (English et al. 2018; Lupi et al. 2020) for computing out-of-pocket cost per person (including fuel costs and miles-related vehicle depreciation) but allow these to vary across the types of vehicles, and where appropriate I include a towing surcharge (English et al. 2019).

3.4.4. Stated Preference Data

To measure total values (both use and non-use values), I use the contingent valuation method. Using a referendum format, the survey asked how people would vote on a one-time income tax that would be used to finance the cost of improving water quality in Michigan's Lower Peninsula and followed many of the steps and logic of the CVM study conducted for the Deepwater Horizon oil spill (Bishop et al. 2017). Each respondent faces only one policy scenario that illustrates a detailed plan for water quality change and the cost required to implement the plan. Several sections introduced and explained the water quality indices and the plan using snippets of text, images and maps, and all information items had interactive questions to reinforce the information. The survey explained that the plan would be paid for by a one-time increase in their income tax (the only cost of the program), and the survey elicited peoples' income before providing them with their cost, which reinforces the consequentiality of the cost. Policy consequentiality was stressed by letting respondents know the survey results would be shared with policy makers and that there was only one option under consideration. Across the sample, the plans differ in where quality scores change, which water quality scores change, and how much each water quality score changes according to an experimental design. Before the vote, respondents were also provided reasons why some people might vote yes or no prior to the vote, and a summary table of plan changes and the cost was again shown.

Stated preference data on tax level by vote confirm the expected monotonic decrease in yes votes as the cost increases. The data show the expected response to price, but it is important to note that the average quality changes across costs are not uniform due to the experimental design. Specifically, the experimental design consisted of 30 scenarios composed of different levels of changes to the water quality attributes shown in Table 3.1.

Table 3.1: Experimental Design for Contingent Valuation: Attributes and Level Changes

Attributes	Level Changes
Clarity Score	0, 5, 10, 15, 20
Water Contact Score	0, 5, 10, 15, 20
Fish and Biomass Score	-5, 0, 5, 20
Wildlife Score	0, 5, 10, 15, 20
One-time Tax (Cost)	\$65, \$195, \$435, \$965

A design that minimized D-error was developed using NGene software. The design was constrained to rule out all indices taking their lowest values of levels of zero. I used the pilot data to estimate mean preferences and standard errors to generate normally distributed Bayesian priors for each preference parameter for the design. Efficient designs tend to increase the precision of parameter estimates for any given sample size, and for efficiency the program tends to assign smaller quality changes to lower cost scenarios and higher quality changes to higher cost scenarios.

3.4.5. Other Demographics Data

The survey collected basic demographic data as a part of the introductory questions (e.g., number of adults in the household along with each adult's sex and age), and at the end of the survey other socio-demographic variables were collected (e.g., employment status, the number of children, education level). Table 3.2 provides the summary statistics of sample characteristics and population characteristics. The median age of the sample falls into the 45–54-year-old category. Although the median age of the entire Michigan population is reported to be 40 in census, the result makes sense because the survey only included adults (18 years or older). The sample age matches that of the census for adults. Half of respondents were four-year college graduates. The proportion of female participants was 52%, similar to that of census data. 50% of respondents reported that they are working full time, lower than the full-time employment rate in Michigan, 61%. Their median household income was 62,500, slightly higher than the median income of Michigan population census tract data, which is 59,584. Our survey also includes statistics for households' structure and demographic variables on household members. Overall, socioeconomic characteristics of the sampled population approximately follow Michigan general population characteristics. That supports the generalizability of value estimates in the following section.

Table 3.2: Sample Characteristics (N = 2,500) and Population Characteristics

	Survey Sample	Census Data
Age>54 (Conditional on Age>18, %)	50	50
College degree (%)	50	30
Female (%)	53	51
Employed (%)	50	61
Median Income ($)	62,500	59,584

3.5. Valuing the Benefits of Ecosystem Services associated with Water Quality Improvement

In this section, three empirical models are introduced to account for both revealed and stated behavior of individuals with respect to water quality improvements. First, the nested logit model quantifies use values of water quality, and it is based on recreational use data from trip elicitation questions along with travel costs to a choice set of sites described by fixed effects that include baseline water quality levels. The second model specifies a binary logit to estimate the total values for water quality improvements from a contingent valuation referendum question for changes in water quality, with no attempt to separately identify use and non-use values. Using this model, I compare the marginal and non-marginal willingness to pay (MWTP) for changes in water quality indices between users and non-users. Lastly, following the theoretical model above, we use a structural model to explore the joint estimation of use and non-use values of water quality improvements that are reflected in revealed behavior on recreational use and contingent valuation data. Using those estimates, I calculate the per choice occasion willingness to pay for the use benefits from the policy proposal and the per choice occasion WTP for the non-use benefits.

3.5.1. A Travel Cost Model of Recreational Choices

Revealed preference data are analyzed in the discrete choice travel cost framework. For each individual i who travels to a recreation site *j*, the conditional indirect utility of direct use of ecosystem services at the site *j* on choice occasion *t* is

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \tag{13}$$

where V_{ijt} is a systematic component of the utility function determined by site attributes and ε_{ijt} is the idiosyncratic error term, representing unobserved attributes of individual i and site *j.* In estimating the recreation demand model, I use both logit and nested logit model and report the results. While the standard logit model imposes considerable structure on the distribution of preferences, the generalized extreme value distribution allows a richer pattern of correlations. As common in the literature, I impose the nesting structure in modeling recreation demand from direct use. The choices available in different groups under a nest are considered to be independent alternatives, while choices within a group (a nest) are assumed to follow the principle of independence of irrelevant alternatives. (1-θ) provides a measure of the degree of correlation among alternatives with nest. In the logit model, θ is equal to 1. In the nested logit model, a higher value of θ implies that alternatives within a nest are more dissimilar to one another, which indicates a stronger correlation between alternative j and alternative k (≠j, for all k in J) within a nest.

The deterministic component of utility does not vary across choice occasions $t \in T = \{1, \dots, T\}$

$$V_{ijt} = V_{ij} = \begin{cases} 0 & \text{if } j = J + 1 \\ \alpha_j + \gamma_c p_{ij} & \text{if } j = 1, \dots, J \end{cases} \tag{14}$$

The utility of the staying at home option is normalized to be zero. Alternative specific constants (α_j) are fixed effects that define non-price attributes in the deterministic component of utility that individuals derive from using recreation site j. The travel cost coefficient γ_c is a travel cost parameter when the cost of visiting a site j is p_{ij}. I denote the travel cost as p_{ij} to prevent the notation confusion with the policy cost c_s, which will be introduced in the joint RP-SP model.

Table 3.3: Discrete Choice Model Estimates – RP Only Model (J = 59; T = 90)

	(1) Logit	(2) Nested Logit
Marginal utility of income (γ_c)	-0.0226*** (0.0002)	-0.0041*** (0.0001)
Dissimilarity coefficient (θ)	1	0.1331*** (0.0021)
WTP per Trip ($-\theta/\gamma_c$)	\$44	\$32
N	2071	2071
Mean Log-likelihood	-40.72	-39.23

Note: The columns (1) and (2) represent different models. Column (1) refers to a simple logit model; Column (2) indicates a nested logit model estimation. Standard errors appear in parentheses. In the column (1), the dissimilarity coefficient is not estimated but set as constant (=1). Choice alternatives with one than one trips were modeled. The number of choice alternatives (J) is 59 and the number of choice occasions (T) is 90 days. *p<0.10; **p<0.05; ***p<0.01

Both the logit and nested logit models indicate a negative and statistically significant price effect on the demand for round-trip recreational activities, with cost coefficients (γ_c) of -0.0026 (s.e. 0.0002) and -0.0041 (s.e. 0.0001), respectively. In addition, the models calculate site-fixed effects defined as alternative specific constants (α_j). The estimated mean marginal WTP for a typical trip is to be US\$44 for the logit model and US\$32 for the nested logit model.

To control unobserved site characteristics when only estimating the site demand model, I adopt a two-stage model suggested by Murdock (2006). The first stage model identifies a full set of alternative specific constants ($\widehat{\alpha_j}$) for all j. The alternative specific constant parameter captures the mean of unobserved site characteristics. The marginal effect of baseline site attributes, in our case water quality q_j, can be identified in the second-stage estimation:

$$\widehat{\alpha_j} = q_j\bar{\beta} + \xi_j \tag{15}$$

Table 3.4: The Effect of Site Attribute (Water Quality) on Site Preference (J = 59; T = 90)

	(1) Logit	(2) Nested Logit
Change in Water Clarity Score (ΔCLS)	-0.0061 (0.0129)	-0.0006 (0.0019)
Change in Water Contact Score (ΔWCS)	0.0049* (0.0105)	0.0008 (0.0015)
Change in Fish Biomass Score (ΔFBS)	0.0269** (0.0269)	0.0046** (0.0018)
Change in Wildlife Score (ΔWLS)	0.0243 (0.0130)	0.0058*** (0.0019)
Constant	-7.5750*** (0.9048)	-3.3642*** (0.1327)
R^2	0.2334	0.3995

Note: Standard errors appear in parentheses. (*p<0.10; **p<0.05; ***p<0.01).

3.5.2. Estimating Total Willingness to Pay for Water Quality Changes

The general model of economic valuation of water quality changes starts from determining the baseline water quality condition and the expected water quality condition under a policy scenario. (Bergstrom, Boyle, and Poe, 2001). For individual i who must decide whether to answer yes or no to a single dichotomous choice question, I use a standard logit model specification using contingent valuation data from the survey. The standard logit model is defined by

$$y_i = 1(y_i^* > 0) \tag{16}$$

where y_i^* is the latent variable determining whether the individual vote yes ($y_i = 1$) or no ($y_i = 0$) to the policy proposal. The latent variable y_i^* is composed of a linear function of observed individual and choice alternative characteristics and an error term η_i follows a standard logistic distribution. The logit model specifies a conditional probability of individual i voting yes as the cumulative distribution function of the logistic distribution. Assuming that the errors are independent draws from the normalized Type I extreme value (or standard Gumbel) distribution, the probability formula is given as

$$Pr_i = Pr[y_i = 1|x_i] = \Gamma(\boldsymbol{x}'\beta) = \frac{exp\ (\boldsymbol{x}'\beta)}{1 + exp(\boldsymbol{x}'\beta)} \tag{17}$$

where y_i is an indicator variable for voting outcome (=1 for individuals voting "yes", = 0 for "no"). **x** is a vector of observed attributes. In the context of our contingent valuation exercise, the indirect conditional utility for the individual with four water quality indices can be rewritten as

$$V(\boldsymbol{x}'\beta) = \beta_0 + \gamma_c C_s + \sum_q \beta_q \Delta q \tag{18}$$

where C_s denotes the price of policy scenario, Δq denotes the change in water quality index q, and water quality data are represented by four water quality indices. Here the notation q was used to indicate one of the water quality variables that are, water clarity score (CLS), water contact score (WCS), fish biomass score (FBS), wildlife score (WLS). Thus, $q \in \{CLS, WCS, FBS, WLS\}$

Table 3.5: Logit Model Estimates – SP Only Model

	Whole Sample	User Group	Non-user Group
Marginal utility of income (γ_c)	-0.0012***	-0.0013***	-0.0011***
Change in Water Clarity Score (ΔCLS)	0.0120**	0.0139**	0.0077
Change in Water Contact Score (ΔWCS)	0.0121**	0.0103	0.0182
Change in Fish Biomass Score (ΔFBS)	0.0174***	0.0108**	0.0300***
Change in Wildlife Score (ΔWLS)	0.0134***	0.0198***	0.0012
Constant	0.3863***	0.5635***	0.0182
N	2,071	1,462	607
Pseudo-R^2	0.037	0.039	0.039

*p<0.10; **p<0.05; ***p<0.01

Table 3.5 presents the results from this analysis. The logit model is estimated first using the full sample and then using the subsample groups *Users* and *Non-users*. 1,462 respondents say that there have been to Michigan waterbodies in Summer 2019, while 607 have not. Having defined the sample of users and non-users based on their use of Michigan waterbodies in three calendar months period in Summer (from June to August 2019), I test whether the coefficients on these variables are identical across each group. Then, I calculate marginal and total willingness to pay for water quality changes. Table 3.6 compares the marginal willingness to pay for water quality improvement (MWTP) between user and non-user groups.

The marginal willingness to pay (MWTP) for a change in index q is given by

$$MWTP_q = -\frac{\beta_q}{\gamma_c} \tag{19}$$

The implicit marginal willingness to pay (MWTP) for a change in Water Clarity Score (CLS) index is $9.9 for a unit increase in CLS index, given by

$$MWTP_{\Delta CLS} = -\frac{\beta_{\Delta CLS}}{\gamma_c} = \frac{0.0120}{-0.0012} = \$9.9$$

whereas the implicit marginal willingness to pay for CLS is $10.7 for users and $7.1 for non-users, calculated based on sub-sample estimates. Likewise, the implicit marginal willingness to pay for a change in Water Contact Score, Fish Biomass Score, and Wildlife Score indices are estimated (See Table 3.6).

Individuals show the highest MWTP for fishing score improvement ($14.4). MWTP for wildlife score improvement ($11.1) and MWTP for water contact score ($10.0) are at a similar level. Then, they are willing to pay the lowest amount for MWTP for water clarity ($9.9). Users show the highest MWTP ($15.4) for water quality improvements for wildlife, whereas non-users value fishing score improvements more ($27.5). It implies the user group cares more about water clarity score and wildlife. The non-user group cared more about water contact and fish biomass score.

Table 3.6: Marginal Willingness to Pay for Water Quality Improvements of Users and Non-users

	Whole Sample	User Group	Non-user Group
MWTP for Water Clarity Score (ΔCLS)	$9.9	$10.7	$7.1
MWTP for Water Contact Score (ΔWCS)	$10.0	$8.1	$13.9
MWTP for Fish Biomass Score (ΔFBS)	$14.4	$8.5	$27.5
MWTP for Wildlife Score (ΔWLS)	$11.1	$15.4	$1.1
N	2,071	1,462	607

Note: MWTP is for per unit increase in each water quality index.

Table 3.7 reports the total willingness to pay (TWTP) for each policy scenario. The total benefits of water quality improvements are the sum across individuals with positive willingness to pay. It shows that the TWTP of non-users are greater than the TWTP of users for the overall change in water quality.

Table 3.7: Total Willingness to Pay for Water Quality Improvements of Users and Non-users

	Whole Sample	User Group	Non-user Group
WTP for a 20-point increase in all indices	\$908	\$857	\$990
WTP for a 15-point increase in all indices	\$681	\$642	\$743
WTP for a 10-point increase in all indices	\$454	\$428	\$495
WTP for a 5-point increase in all indices	\$227	\$214	\$247
WTP for a 5-point decrease in all indices	-\$227	-\$214	-\$214
N	2,071	1,462	607

The use of stated preference data in this approach demonstrates one of the simple *ad-hoc* methods that are commonly used in the literature to estimate use and non-use values by defining groups of users and non-users. The approach involves defining two distinct groups of individuals and the groups are identified and distinguished based on their participation in a related water-based recreational activity. By incorporating information about whether an individual has visited a site for water-based recreational purposes or not, this method allows for a more nuanced understanding of how users value and utilize a particular resource and how non-users do.

3.5.3. Joint RP-SP Estimation of Use and Non-use Values

The objective of the econometric model that is introduced here is to simultaneously estimate use and non-use values using both RP and SP data (Day et al. 2019). First, the conditional indirect utility function is now specified in an additively separable form.

$$u_{i,t,s|j} = v_{i,t,s|j}^{Use} + v_{i,t,s}^{NonUse} + v_{i,t,s|j}^{other} + \varepsilon_{i,j,t,s} \tag{20}$$

where $v_{i,t,s|j}^{Use}$ is the conditional indirect utility from recreation activities at site j and $v_{i,t,s}^{NonUse}$ is the non-use utility gain from J different sites, independent of the recreation activity, and $v_{i,t,s|j}^{other}$ is the utility from a composite good. All of the conditional indirect utility terms (i.e., the v's) are constant over choice occasions, which will substantially simplify some terms below. The error terms are allowed to vary over choice occasions.

Following the specification and assumption made in the theoretical motivation, each of the components is expressed as below.

$$v_{i,t,s|j}^{Use} = \begin{cases} \alpha_{ijt} + q_{js}\beta_i & \text{if } j = 1, 2, \dots, J \\ \alpha_{i,J+1,t} & \text{if } j = J + 1 \end{cases} \tag{21}$$

When individual *i* evaluates the option of visiting visit site *j* on a choice occasion *t*, the conditional use utility of visiting site *j* among J sites is a linear combination of alternative specific constant α_{ijt} and site quality q_{js}. When individual *i* evaluates the option to "not go" to any site at a choice occasion at *t*, the conditional use utility for such opt-out choice *J+1* does not include quality and is given by $\alpha_{i,J+1,t}$.

Non-use utility is characterized by the distance weighted sum across all the non-use utility gained from sites $j = 1$ to $j = J$. This specification imposes an assumption that non-use utility has no substitution or complementarity relationships among sites and is given by:

$$v_{i,t,s}^{NonUse} = \sum_{j=1}^{J} \left(d_{ij} + 1\right)^{\lambda_i} (a_{ijt} + q_{js} b_i) \tag{22}$$

where λ_i is a parameter of the rate of distance decay in non-use utility. The value of λ_i determines how non-use utility may change with respect to distance.

Finally, the conditional utility from other consumption is assumed to be linear in expenditure.

$$v_{i,t,s|j}^{other} = \gamma_i (y_{i,t} - p_{i,j} - c_s) \tag{23}$$

where γ_i is a parameter of the marginal utility of money and $y_{i,t} - p_{i,j} - c_s$ is the expenditure available for composite goods at choice occasion *t*. Note that c_s is the lump-sum tax required for a policy change C_s divided by the total number of choice occasions T.

3.5.3.1. Revealed Preference Portion of the Structural Model

In modeling the RP data, I focus on the baseline period (i.e., without a policy change in the water quality variables), so that $q_{i,j,0} = q_{j,0}$ for all individuals. Moreover, there is no policy fee, so $c_{i,0} = 0$ for all *i*. In this case, the probability that individual *i* will choose alternative j on choice occasion t is given by:

$$\begin{aligned} Pr_{i,j,t,0} &= Pr\left(u_{i,t,0|j} - u_{i,t,0|k} > 0\right) \\ &= Pr\left[\left(v_{i,0|j}^{Use} + v_{i,0}^{NonUse} + v_{i,0|j}^{other}\right) - \left(v_{i,0|k}^{Use} + v_{i,0}^{NonUse} + v_{i,0|k}^{other}\right)\right. \\ &\qquad \left. > \ \varepsilon_{i,k,t,0} - \varepsilon_{i,j,t,0}\ \right] \end{aligned} \tag{24}$$

where $\left(v_{i,0|j}^{Use} + v_{i,0|j}^{other}\right) - \left(v_{i,0|k}^{Use} + v_{i,0|k}^{other}\right) = v_{i,0|j}^{RP} - v_{i,0|k}^{RP}$ as adding α_{J+1} term does not change the equality. Thus, the LHS of the inequality $(u_{it0|j} - u_{it0|k})$ in the probability function can be rewritten as $v_{i,0|j}^{Use} + v_{i,0|j}^{other} - v_{i,0|k}^{Use} - v_{i,0|k}^{other} = v_{i,0|j}^{RP} - v_{i,0|k}^{RP}$ where $v_{i,s|j}^{RP} = \alpha_{ij0} - \alpha_{J+1} + q_{ijs}\beta_i - \gamma_i p_{ij} = \widetilde{\alpha_J} - \gamma_i p_{ij}$.

By imposing that $v_{i,s|J+1}^{RP} = 0$ or $p_{i,J+1} = 0$ and $q_{i0}\beta_i = 0$, normalize the no trip (staying at home) utility if *j* = *J*+1. Thus, the choice probability of individual *i* visiting site *j* at the choice occasion *t* under the baseline water quality condition (s=0) is

$$\begin{aligned} Pr_{i,j,t,0} &= Pr\left(u_{i,t,0|j} - u_{i,t,0|k} > 0\right) \\ &= Pr\left[v_{i,0|j}^{RP} - v_{i,0|k}^{RP} > \varepsilon_{i,k,t,0} - \varepsilon_{i,j,t,0}\right] = Pr_{i,j,0} \end{aligned} \tag{25}$$

3.5.3.2. Adding SP Data with Non-use Values to the Structural Model

Next, I add SP data with non-use values in the model. The annual utility that individual *i* receives from choosing from policy scenario s (*s* = 0,1) is

$$u_{i,\cdot,s} = \tilde{v}_{i,\cdot,s} + \tilde{\varepsilon}_{i,\cdot,s} = \sum_{t=1}^{T} \tilde{v}_{i,s} + \sum_{t=1}^{T} \tilde{\varepsilon}_{i,s} = T\tilde{v}_{i,s} + \sum_{t=1}^{T} \tilde{\varepsilon}_{i,s} \tag{26}$$

where

$$\tilde{v}_{i,s} = \mathbb{E}\left[\max_j\left(v_{i,s|j}^{Use} + v_{i,s|j}^{other} + \varepsilon_{i,j,t,s}^{Use}\right)\right] + \frac{v_{i,0}^{NonUse}}{\sigma^{SP}} \tag{27}$$

Since the expected maximum utility takes a logsum form (plus a constant), the utility function can be rewritten as

$$\tilde{v}_{i,s} = \frac{1}{\sigma^{SP}} \ln\left[\sum_{j=1}^{J+1} \exp\left(v_{i,s|j}^{Use} + v_{i,s|j}^{other}\right)\right] + \kappa + \frac{v_{i,0}^{NonUse}}{\sigma^{SP}} \tag{28}$$

The scale parameter σ^{SP} characterizes the relative variation in the SP data compared to the RP data. In general, I expect SP data to show greater variability than RP data (i.e., $\sigma^{SP} > 1$).

$$\varepsilon_{i,j,t,s}^{Use} \sim \text{i.i.d}\ EV(0, \sigma^{SP})\ \ \forall\ i, j, t, s \tag{29}$$

Rewriting this equation, the conditional indirect utility function takes a sum of indirect utility functions over all the choice occasion from *t =1* to *t = T*.

$$u_{i,\cdot,s} = \tilde{v}_{i,\cdot,s} + \tilde{\varepsilon}_{i,\cdot,s} = \sum_{t=1}^{T} \tilde{v}_{i,s} + \sum_{t=1}^{T} \tilde{\varepsilon}_{i,s} = T\tilde{v}_{i,s} + \sum_{t=1}^{T} \tilde{\varepsilon}_{i,s}$$

$$= T \cdot \left\{ \frac{1}{\sigma^{SP}} \ln \left[\sum_{j=1}^{J+1} \exp\left(v_{i,s|j}^{Use} + v_{i,s|j}^{other}\right) \right] + \kappa + \frac{v_{i,s}^{NonUse}}{\sigma^{SP}} \right\} + \sum_{t=1}^{T} \tilde{\varepsilon}_{i,s} \tag{30}$$

$$= \frac{T}{\sigma^{SP}} \left\{ \ln \left[\sum_{j=1}^{J+1} \exp\left(v_{i,s|j}^{use} + v_{i,s|j}^{other}\right) \right] + \kappa + v_{i,s}^{NonUse} \right\} + \sum_{t=1}^{T} \tilde{\varepsilon}_{i,s}$$

where κ is a constant.

The probability that individual *i* would choose the proposed scenario $s = 1$ would be

$$Pr\left(u_{i,\cdot,1} > u_{i,\cdot,0}\right) = Pr\left(\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0} > \tilde{\varepsilon}_{i,\cdot}\right)$$

$$= Pr\left(\tilde{v}_{i,\cdot,1} + \tilde{\varepsilon}_{i,\cdot,1} > \tilde{v}_{i,\cdot,0} + \tilde{\varepsilon}_{i,\cdot,0}\right)$$

$$= \Pr(\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0} > \tilde{\varepsilon}_{i,\cdot,0} - \tilde{\varepsilon}_{i,\cdot,1}) \tag{31}$$

$$= \Pr(\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0} > \tilde{\varepsilon}_{i,\cdot})$$

$$= F_{\tilde{\varepsilon}}(\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0})$$

where $F_{\tilde{\varepsilon}}$ denotes to the cumulative distribution function for $\tilde{\varepsilon}_{i,\cdot} = \tilde{\varepsilon}_{i,\cdot,0} - \tilde{\varepsilon}_{i,\cdot,1}$, so that

$$\tilde{\varepsilon}_{i,\cdot} = \sum_{t=1}^{T} (\tilde{\varepsilon}_{i,t,0} - \tilde{\varepsilon}_{i,t,1}) \tag{32}$$

If $\tilde{\varepsilon}_{i,\cdot} = \tilde{\varepsilon}_{i,\cdot,0} - \tilde{\varepsilon}_{i,\cdot,1}$ follows a logistic distribution (0,1), then George and Mudholkar (1983) establishes that $F_{\tilde{\varepsilon}}$ is distributed as $t_{5T+4}(0, \tau)$ where $\tau = \pi\sqrt{\frac{5T^2+2T}{15T+12}}$.

$$\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0} = \frac{T}{\sigma^{SP}}\left\{\ln\left[\sum_{j=1}^{J+1}\exp\left(v_{i,1|j}^{Use} + v_{i,1|j}^{other}\right)\right] + \kappa + v_{i,1}^{NonUse}\right\}$$

$$- \frac{T}{\sigma^{SP}}\left\{\ln\left[\sum_{j=1}^{J+1}\exp\left(v_{i,0|j}^{Use} + v_{i,0|j}^{other}\right)\right] + \kappa + v_{i,0}^{NonUse}\right\} \tag{33}$$

$$= \frac{T}{\sigma^{SP}}\left\{\ln\left[\sum_{j=1}^{J+1}\exp\left(\tilde{\alpha}_j + \Delta q_{i,j,1}\beta - \gamma p_{ij}\right)\right] + v_{i,1}^{NonUse} - \ln\left[\sum_{j=1}^{J+1}\exp\left(\tilde{\alpha}_j - \gamma p_{ij}\right)\right] - \gamma c_{i1} - v_{i,0}^{NonUse}\right\}$$

Note $\Delta q_{i,j,0} = 0$ and $c_{i0} = 0$ because there is no cost burden on the baseline condition. Combining the results thus far,

$$\begin{aligned}
\Pr\left(u_{i,\cdot,1} > u_{i,\cdot,0}\right) &= \Pr(\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0} > \tilde{\varepsilon}_{i,\cdot}) \\
&= F_{\tau}(\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0}) \\
&= F_{\tilde{\varepsilon}}\left[\frac{T}{\sigma^{SP}}\left\{\ln\left[\frac{\sum_{j=1}^{J+1}\exp\left(\tilde{\alpha}_j + \Delta q_{i,j,1}\beta - \gamma p P_{ij}\right)}{\sum_{j=1}^{J+1}\exp\left(\tilde{\alpha}_j - \gamma p_{ij}\right)}\right] + v_{i,1}^{NonUse} - v_{i,0}^{NonUse} - \gamma c_{i1}\right\}\right]
\end{aligned} \tag{34}$$

The relevant probability function for the SP dichotomous choice becomes

$$Pr\left(u_{i,\cdot,1} > u_{i,\cdot,0}\right) = F_{\tilde{\varepsilon}}\left[\frac{T}{\sigma^{SP}}\left\{\ln\left[\frac{\sum_{j=1}^{J+1}\exp\left(\tilde{\alpha}_j + \Delta q_{i,j,1}\beta - \gamma p_{ij}\right)}{\sum_{j=1}^{J+1}\exp\left(\tilde{\alpha}_j - \gamma p_{ij}\right)}\right] + \sum_{j=1}^{J}\left(d_{ij}+1\right)^{\lambda_i}\left(\Delta q_{i,j,1}b_i\right) - \gamma c_{i1}\right\}\right] \tag{35}$$

as the difference between utilities before policy and after policy is

$$\begin{aligned}
v_{i,1}^{NonUse} - v_{i,0}^{NonUse} &= \left[\sum_{j=1}^{J}\left(d_{ij}+1\right)^{\lambda_i}\left(a_{ijt} + q_{j1}b_i\right)\right] - \left[\sum_{j=1}^{J}\left(d_{ij}+1\right)^{\lambda_i}\left(a_{ijt} + q_{j0}b_i\right)\right] \\
&= \sum_{j=1}^{J}\left(d_{ij}+1\right)^{\lambda_i}\Delta q_{i,j,1}b_i
\end{aligned} \tag{36}$$

The resulting likelihood function characterizes individual *i*'s revealed preference for recreational sites along with their stated preference choices under the random utility model framework.

$$L_i(\boldsymbol{\theta}_i) = \prod_t\prod_j Pr_{i,j,t}\left(\boldsymbol{\theta}_i^{\boldsymbol{Use}}, \gamma_i\right)^{Y_{i,j,t}}\prod_s Pr_{i,s}\left(\boldsymbol{\theta}_i^{\boldsymbol{Use}}, \boldsymbol{\theta}_i^{\boldsymbol{NonUse}}, \gamma_i\right)^{Y_{i,s}} \tag{37}$$

where $\boldsymbol{\theta}_i$= [$\boldsymbol{\theta}_i^{Use}$, $\boldsymbol{\theta}_i^{NonUse}$, $\boldsymbol{\gamma}_i$] are parameters of the behavioral model. $\boldsymbol{\theta}_i^{Use} = [\alpha_1, \ldots., \alpha_J, \beta_i]$ denote the parameters of the use element of individual *i*'s utility and $\boldsymbol{\theta}_i^{NonUse} = [\, b_i, \lambda_i]$ denote the identifiable parameters of the non-use element of utility. The maximum log-likelihood estimation program will solve

$$L_{SP} = \log\big(L_i(\boldsymbol{\theta}_i)\big) = Y_i^{SP} \ln\big[F_{\tilde{\varepsilon}}\big((\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0})\big] + \big(1 - Y_i^{SP}\big) \ln\big[1 - F_{\tilde{\varepsilon}}\big((\tilde{v}_{i,\cdot,1} - \tilde{v}_{i,\cdot,0})\big] \qquad (38)$$

3.6. Estimation Results and Discussion

This section presents a comparison of estimates from three models. These models include the use utility estimates from revealed preference only data, the total utility estimates from stated preference data, and both use and non-use utility estimates from the joint RP and SP structural model.

3.6.1. Joint RP and SP Model Results

The structural estimation strategy discussed in Section 3.5.3 offers two additional benefits. Firstly, it enables us to identify detailed use-utility parameters that provide improved information on the qualities of recreational sites and use utility from various types of recreation trips. Secondly, this model can identify non-use utility related parameters such as the non-use utility portion of site quality effect and distance decay parameters.

To expedite program running time and improve convergence, two different approaches were used to run the joint revealed preference-stated preference model: (1) the Joint RP-SP Model and (2) the Sequential RP-SP Model. For the joint RP-SP model, the RP only model estimates were used as initial values. All parameter estimates, including alternative specific constants, cost parameter, nesting parameter, and quality parameters, were estimated simultaneously all at once using maximum likelihood estimation. The sequential RP-SP model involves running the RP only model first. Then, the first stage RP only model estimates, including alternative specific constants and cost parameters, are used as fixed values in the second stage RP-SP model when estimating equation (38).

When attempting to jointly estimate all the parameters together, the program takes a long time and eventually hits the estimation limit. At that point it was observed that the estimates for both the use and non-use quality parameters did not deviate significantly from the initial values set by the analyst in the estimation routine. The estimates of alternative specific constants (ASCs), denoted as $\alpha_1, \dots, \alpha_J$ in mathematical notation, showed significant variation and converged to values consistent with the RP-only model estimates in the first stage, however, some of the key parameters of interest (β, b, λ) that were being estimated in the second stage did not vary significantly and did not converge. After 500 runs, the estimate of the scaling factor parameter estimate $(\hat{\sigma})$ approximated to 1.7. However, the program was unable to report the standard error for each parameter as the covariance matrix of the parameters was unable to invert. The computed covariance matrix of the parameters was obtained through the inverse of the Hessian matrix method. However, due to the long estimation time and non-convergence of the joint RP-SP model, at the iteration limit of 500 runs, the empirical results were inconsistent with theoretical expectations. Although the maximum likelihood estimation routine was verified and the estimation code was inspected using the simulation study, the program still faces convergence issues under various specifications.

With the joint model having convergence issues, I opted to use the first stage RP only model estimates (the alternative specific constants and cost parameters; $\alpha_1, \dots, \alpha_J$, and β) as constant values in the second stage RP-SP model when estimating equation (38). I call it the sequential RP-SP model to avoid confusion with the two-step estimation of RP only model in section 3.5.2. In the first stage of the sequential RP-SP model, I run a RP only model and read in the estimates from the RP only estimation into the probability function for the SP dichotomous choice (eq. 35) of the second stage maximum likelihood function (eq. 38) to estimate use quality parameter estimates $(\hat{\beta})$ and non-use quality parameter estimates $(\hat{b})$, that implies marginal use and non-use utility of quality change, along with σ for relative variance scales.

For estimation holding the scaling parameter constant, Table 3.8 reports the quality parameter estimates for each water quality index $(\widehat{\beta_{CLS}}, \widehat{\beta_{WCS}}, \widehat{\beta_{FBS}}, \widehat{\beta_{WLS}}, \widehat{b_{CLS}}, \widehat{b_{WCS}}, \widehat{b_{FBS}}, \widehat{b_{WLS}})$ upon hitting the 10,000 iteration limit. For all indices, the use quality parameter estimates are negative but slightly less than 0, while the non-use quality parameter estimates are positive but sometimes their magnitude is one tenth of the magnitude of the use quality parameter. The result is counterintuitive, since the negative estimate for the use quality parameter suggests that people prefer waterbodies with lower clarity for recreational use, which contradicts the survey data and the RP only model results. An additional noteworthy observation in this table is the positive estimate for the non-use quality parameter. The result implies that individuals have a preference for waterbodies with higher water quality scores, even if they do not use the water body for recreation.

Table 3.8: Sequential RP-SP Model Results - Stage 2 Estimates for Four Water Quality Indices (σ = 2)

	Use quality parameter estimates ($\hat{\beta}$)	Non-use quality parameter estimates ($\hat{b}$)	Scaling factor parameter estimate ($\hat{\sigma}$)
Clarity Score (CLS)	-0.005 (0.021)	0.000 (0.002)	2
Water Contact Score (WCS)	-0.040 (0.026)	0.004 (0.002)	2
Fish Biomass Score (FBS)	-0.003 (0.018)	0.004 (0.002)	2
Wildlife Score (WLS)	-0.010 (0.020)	0.004 (0.002)	2
No. of Observations	2071		
No. of Iterations⁋	10000		
Mean log-likelihood	-0.6762		

⁋Note: maximum number of iterations exceeded.

The failure of the sequential RP-SP model to converge could have resulted from a variety of factors, such as data issues, model specification errors in the model, or optimization problems. To address this issue and improve the model's performance, I examined the problem and implemented an approach by running the sequential RP-SP model separately for each water quality index at a time.

Table 3.9 displays the results from the second stage estimation of the sequential RP-SP model for each of the four water quality indices separately. The table presents the estimates for both use and non-use quality parameter and scaling factor parameter. The results confirm that the use quality parameter estimates ($\hat{\beta}$) are negative for all four water quality measures, while the non-use quality parameter estimates ($\hat{b}$) are positive. The estimated use and non-use quality parameter for all indices are both -0.03 and 0.04, respectively, and are statistically significant at a 1% significance level. The result is counter intuitive because the negative use quality parameter estimate ($\hat{\beta}$ = -0.03) implies that people prefer lower water quality for recreational activities than waterbodies with higher quality. Similar to the previous table, Table 3.9 also shows positive and statistically significant non-use quality parameter estimates for all four water quality indices. The magnitude of the non-use quality parameter estimates ranges from 0.043 to 0.048 ($\hat{b}$ = 0.04). Most non-use quality parameters were statistically significant, indicating that people's preferences for water quality not only affect the use of waterbodies but also their affects their non-use values for waterbodies. People would prefer better water quality for waterbodies, regardless of whether they use them or not. Lastly, the estimated scaling factor is 0.52, indicating that the variability observed in RP data is higher than that in SP data.

Table 3.9: Sequential RP-SP Model Results - Stage 2 Estimates for Each Water Quality Index (When running, the model with one index at a time)

	Use quality parameter estimate ($\hat{\beta}$)	Non-use quality parameter estimate ($\hat{b}$)	Scaling factor parameter estimate ($\hat{\sigma}$)	No. of Iterations	Mean log-likelihood
(1) Clarity Score	-0.034*** (0.110)	0.043*** (0.006)	0.530*** (0.096)	39	-0.68
(2) Water Contact Score	-0.036*** (0.000)	0.048*** (0.000)	0.524*** (0.090)	45	-0.68
(3) Fish Biomass Score	-0.032*** (0.004)	0.043*** (0.000)	0.653*** (0.126)	1106	-0.68
(4) Wildlife Score	-0.030*** (0.000)	0.048*** (0.000)	0.524*** (0.090)	17	-0.68
No. of Observations	2071				

Note: Standard errors appear in parentheses. (*p<0.10; **p<0.05; ***p<0.01).

To ensure the robustness of the results, I perform multiple checks under two different model specifications. The program algorithm is set up similarly to previous tables, where the first stage of the joint model begins with a random utility travel cost logit fixed effects model. The second stage involves solving the maximum likelihood function of stated preference choices given the recreational site choices in the first stage. The key difference from the previous model specifications in this robustness check is that the scaling factor parameter is assumed to be a constant. The following tables, Tables 3.10 and 3.11, present a comparison of the second stage results under different assumptions for the fixed scaling factor parameter (σ), an assumption that can be critical when the model is not particularly well-defined. Due to the absence of universal techniques for computing initial values for the scaling factor parameter, it may be important to explore various scaling factor parameter values while attempting to estimate it. Under this specification, where the variability of SP data is assumed to be greater than that of RP data, which is a common assumption in other combined RP-SP studies, the estimates of use quality parameter and non-use quality parameter remain negative and positive respectively.

Table 3.10: Sequential RP-SP Model - Stage 2 Estimates for Each Water Quality Index (σ = 1.5)

	Use quality parameter estimate ($\hat{\beta}$)	Non-use quality parameter estimate ($\hat{b}$)	Scaling factor parameter (σ)	No. of Iterations	Mean log-likelihood
(1) Clarity Score	-0.090** (0.039)	0.007*** (0.001)	1.5	430	-0.6826
(2) Water Contact Score	-0.901*** (0.035)	0.008*** (0.001)	1.5	461	-0.6812
(3) Fish Biomass Score	-0.054*** (0.019)	0.007*** (0.001)	1.5	375	-0.6800
(4) Wildlife Score	-0.079*** (0.032)	0.007*** (0.001)	1.5	491	-0.6810
No. of Observations	2071				

Note: Standard errors appear in parentheses. (*p<0.10; **p<0.05; ***p<0.01).

Table 3.11: Sequential RP-SP Model - Stage 2 Estimates for Each Water Quality Index (σ = 2)

	Use quality parameter estimate ($\hat{\beta}$)	Non-use quality parameter estimate ($\hat{b}$)	Scaling factor parameter (σ)	No. of Iterations	Mean log-likelihood
(1) Clarity Score	-0.113* (0.060)	0.008*** (0.001)	2	268	-0.6839
(2) Water Contact Score	-0.109*** (0.049)	0.010*** (0.000)	2	236	-0.6827
(3) Fish Biomass Score	-0.061*** (0.023)	0.009*** (0.001)	2	188	-0.6811
(4) Wildlife Score	-0.101** (0.050)	0.009*** (0.001)	2	235	-0.6823
No. of Observations	2071				

Note: Standard errors appear in parentheses. (*p<0.10; **p<0.05; ***p<0.01).

3.6.2. Evidence from Separate Revealed and Stated Preference Water Quality Valuations

In this subsection, I provide evidence on use value estimates obtained through revealed preference data and on total values obtained through contingent valuation stated preference data. To estimate the travel cost parameter and site fixed effects using revealed preference data, I employ a two-step estimation method that takes into account the unobserved characteristics of recreation areas. This two-step approach ensures unbiased travel cost parameters and produces correct welfare estimates (Murdock, 2006). The stated preference data was modeled separately for those classified as users and non-users. If users and non-users hold the same non-use value, then the expectation is that the user group will have larger total WTP than the non-user group. In the empirical application, Table 3.12 shows that a 5 point increase in all indices results in a higher WTP ($247) for the non-user group than the user group's total WTP ($214). This result suggests there is preference heterogeneity between the groups. Table 3.12 also shows the WTP from the stated preference data for a model run on the whole sample ($227), which lies between the results when the groups are separated.

Table 3.12: Recreational and Total Valuation of Water Quality for the 2019 Season

A. Revealed Preference Valuation	Mean WTP per trip
Value of a trip (Logit)	$44
Value of a trip (Nested Logit)	$32
B. Contingent Valuation	WTP for a 5-point increase in all indices
Whole sample WTP	$227
User group WTP	$214
Non-user group WTP	$247

3.6.3. Implications for Water Quality Valuation

In this study, I analyzed recreation demand for sites with different water quality using both revealed preference (RP) and stated preference (SP) models. I estimated the marginal willingness-to-pay (WTP) of both users and non-users for improvements in water clarity, water contact, fishing, and wildlife condition using the RP only and SP only models separately. My findings indicate that people value improvements in recreational fishing aspects of water quality the most. However, to further validate the welfare measure, it is necessary to concentrate future effort on two other models, which may produce dissimilar results.

For welfare analysis for non-use values, researchers have traditionally used a back-of-the-envelope calculation by subtracting the use value estimates from the total value estimates derived from SP studies. The joint RP-SP structural model allows for the separate identification of parameters for the conditional indirect utility of use, non-use, and composite goods. Unfortunately, this joint RP-SP structural model, which includes over 50 fixed effects, has faced major convergence issues, similar to the Monte Carlo simulation results in Essay 2 for some parameter spaces. As a result, I explore the possibility of a sequential two stage RP-SP model estimation to enhance the validity of the welfare measure.

This presented model has the potential to be applied in other non-market valuation studies that involve both use and non-use benefits. To adapt the model to such studies, researchers would need to determine the appropriate spatial configuration and gather data on both revealed. and stated preferences. It can provide a quantification of the use and non-use value ratio. However, there are some limitations to this model that warrant further investigation. Compared with other methodologies proposed in previous literature, the data collection process for this methodology is more expensive and the implementation of the methodologies can be challenging. Furthermore, as demonstrated in the first two essays, the estimation process is subject to significant limitations and can be sensitive to the data type and the preferences of the population being studied. Therefore, there is a need for further research in this area.

3.7. Summary and Conclusion

This paper presents a structurally consistent model to estimate use and non-use values in a utility theoretic way, and it is applied to evaluate the benefits of water quality improvements in Michigan watersheds. This model incorporates high-resolution ecological data on ecosystem responses to changes in water quality and provides a more comprehensive understanding of the benefits of water quality improvements. To estimate the marginal willingness to pay for water quality improvements, four water quality indices are developed to capture different aspects of water quality change, and they are presented in the survey. The estimates derived from the structural model can be employed to determine the average welfare gains resulting from water quality improvements. Based on the evidence on use and non-use share allocation submitted by survey respondents, I observe that there are significant non-use components in the total value of water quality improvements. This suggests that individuals derive value from both use and non-use aspects.

This study aims to evaluate the welfare gains from water quality improvements by utilizing a structural model of use and non-use values. The US EPA has identified the delineation of use and non-use values as a key policy need for its cost-benefit analyses of water quality regulations. The proposed joint revealed and stated preference model combines the random utility travel cost model of recreation demand and the contingent valuation method, and it measures and identifies both use and non-use values for changes in water quality. Moreover, the proposed model includes a more comprehensive set of recreation site fixed effects to improve the precision of use valuation estimation. This enhancement expands upon the work of Day et al. (2019), which only consider the alternative specific constant for the no-trip option.

I apply the model to an empirical application using recently collected recreation use and survey referendum data from an address-based push-to-web survey of the Michigan general population. Data for several alternative methods for separating use and non-use values that have appeared in the literature were collected in the survey. The recreation demand model contributes to the literature and policymaking by estimating use values from a full panel of water-based recreation trips at all types of waterbodies in and surrounding Michigan using a nested logit specification of the repeated site choice decisions. The contingent valuation portion uses a consequential referendum format to estimate total values of small and large changes in Michigan's water quality addressing a gap in the valuation literature that rarely covers small changes.

Through empirical estimation of joint RP-SP structural model, I have discovered a negative marginal utility of use and a positive marginal utility of non-use. However, the structural estimation of use and non-use values presents several empirical challenges, and as such, I do not recommend this structural approach to other researchers unless their research design contains multiple-choice tasks to allow sufficient variability in stated preference data. The joint RP-SP model may be more effective in studies with a more extensive experimental design for the stated preference model than those commonly used in an SP-only study. Such an experimental design could address the convergence and identification issues identified in the application section of this paper. Finally, structural model proposed here may work better under some more general model assumptions which admit some heterogeneity in preferences and still allows the use and non-use estimates to be identified.

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