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Total Economic Valuation of Great Lakes Recreational Fisheries: Attribute Non-attendance, Hypothetical Bias and Insensitivity to Scope

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Abstract. We use stated preference methods to estimate willingness to pay to avoid reductions in recreational catch in Great Lakes fisheries. We compare willingness to pay estimates where uncertain "in favor" votes are recoded to "against" votes to an attribute non-attendance model that focuses on the policy cost attribute. We find that the two hypothetical bias models yield similar results. We estimate another attribute non-attendance model that also considers the scope of the policy and find that the scope elasticity is significantly underestimated in other models. The willingness to pay in this last model is higher than in the other models.

Key Words: Attribute non-attendance, Hypothetical bias, Scope test, Willingess to pay

Introduction

The Great Lakes consist of Lake Erie, Lake Huron, Lake Michigan, Lake Ontario and Lake Superior. Great Lakes tributaries and connecting waters include the Detroit River, the St. Mary's River, the Niagara River, Lake St. Clair, the St. Clair River and the St. Lawrence River. Having well-balanced and productive fish populations are important for supporting recreational fisheries in the Great Lakes, where each year, almost 1.4 million anglers fish these waters (Cornicelli et al. 2022). There are a number of important recreational fish species in the Great Lakes. Warm-water species are found in the shallower bays and nearshore areas. The most important warm-water species for recreation are: Yellow Perch, Black Bass (Largemouth, Smallmouth), Walleye, and Pike (Northern Pike, Muskelunge). Cold-water species are found in deeper, open waters. The most important cold-water species for recreation are: Salmon (Chinook, Coho), Steelhead (Rainbow Trout), Lake Trout and other trout (Brook, Brown). There are a number of environmental stressors that threaten the sustainable recreational harvest of these species. Climate change, loss of wetlands, agricultural runoff, municipal waste water runoff, algae blooms, aquatic invasive species and industrial pollution all contribute to the problem. Fishery managers cooperatively manage fisheries in the Great Lakes by stocking predator fishes like salmon and trout, by regulating harvest and by enforcement of fishing regulations.

The purpose of this study is to estimate the total economic value held by households who live in the U.S. Great Lakes states and Ontario, Canada for maintaining recreational fishery catch. We fielded a stated preference survey of the general public using the Dynata online panel and the Qualtrics survey platform. A referendum-style discrete choice experiment is designed to estimate the value of various management measures that affect Great Lakes fisheries catch rates

(Boyle et al. 2016; Giguere, Moore and Whitehead, 2020).

The sample of the general public includes users (e.g., anglers) and non-users of Great Lakes fisheries. Stated preference demand models are employed to quantify the economic values that these two groups hold for Great Lakes fisheries management. A number of stated preference studies have been conducted for Great Lakes resources (e.g., Knoche and Lupi, 2016; Zhang and Sohngen, 2018; Howard et al. 2017; Hunt et al., 2020; Lauber et al., 2020; Raynor and Phaneuf, 2020; Ready et al. 2018). These studies focus on use values of recreational anglers and none of these studies estimate the total economic value of Great Lakes fishery resources. Only Whitehead et al. (2009) have considered the preferences of non-users of Great Lakes resources. A consideration of non-users is important since this demographic may hold significant economic values for Great Lakes fishery resources and non-users are a major portion of the public.

We investigate two other important valuation issues. First, stated preference data is prone to hypothetical bias due to incentive incompatibility, yea-saying and other common survey maladies. Hypothetical bias is a general term that describes differences between stated and revealed preferences. Hypothetical bias is pervasive in contingent valuation (Hausman 2012, Haab et al. 2013) but has also been identified in discrete choice experiments (Taylor, Morrison, and Boyle 2010; Fifer, Rose and Greaves 2014). Several approaches have been developed to mitigate hypothetical bias in contingent valuation (Penn and Hu 2018). There is a growing choice experiment literature that applies hypothetical bias mitigation approaches from the stated preference literature (e.g., Ready, Champ, and Lawton 2010, Howard et al. 2017). In this study we ask respondents who indicate that they are willing to pay for the policy with a certainty scale question and recode votes “in favor” to votes “against” in order to mitigate hypothetical bias

(Penn and Hu 2018) and consider an attribute non-attendance hypothetical bias model (Koetse 2017).

Second, insensitivity to the scope of the policy is a potential issue in stated preference data (Hausman 2012, Haab et al. 2013). A number of studies exhibit scope insensitivity in split-sample tests, violating an axiom of consumer preferences (Desvousges, Mathews and Train 2012). Desvousges, Mathews and Train (2012) suggest that the magnitude of scope effects must be somehow “adequate.” Alternatively, Whitehead (2016) has proposed that scope elasticity be used to measure the economic significance of the sensitivity of willingness to pay to the scope of the policy and that mere “plausibility” is a necessary condition for passage of the test. Dugstad et al. (2021) extend the concept of scope elasticity and plausibility to discrete choice experiments. In this study we estimate the scope elasticities in a variety of models to assess the validity of the stated preference data and each model.

Third, we consider attribute non-attendance, where survey respondents ignore certain attributes in an attempt to simplify complex choice tasks (Lew and Whitehead 2020). Attribute non-attendance can lead to biased willingness to pay estimates. Two broad approaches have been developed to identify and mitigate attribute non-attendance. Stated attribute non-attendance models use respondents’ own admissions of ignoring attributes. Inferred attribute non-attendance models use results from heterogeneous preference models to estimate those who ignore attributes. Several empirical strategies have been developed to incorporate these methods into valuation models. Campbell, Hensher and Scarpa (2011) use a latent class model to estimate separate classes of respondents who ignore attributes. Attribute coefficients are fixed at zero in the ignoring class and the model sorts respondents into non-attending classes. Class probabilities provide estimates of those respondents who ignore one of the attributes. Stated ANA models rely on survey respondent statements about which attributes they ignored. Scarpa et al. (2012) compare these approaches and find mostly similar results. Kragt (2013) finds that the stated and inferred approaches produce different results and that the inferred approach is statistically preferred.

We use the equality constrained latent class model (ECLC) form of the inferred attribute non-attendance models. Koetse (2017) uses the ECLC model to consider whether hypothetical bias, as measured by ANA on the cost variable, is responsible for differences in WTP and willingness to accept. In this model, only the coefficient on the cost variable is constrained to zero. We compare this to the certainty corrected hypothetical bias mitigation strategy. We find that the equality constrained latent class model that considers both the cost and scope variables statistically outperforms all other models and generates greater sensitivity to the scope of the policy. This model also produces the highest willingness to pay estimates.

In the next section of the paper we describe the valuation survey and summarize the data. Following a description of the empirical model we present the regression, willingness to pay and scope elasticity results. In conclusion, we present aggregate benefit estimates, discuss the results and suggest directions for future research.

Valuation Survey

Following a review of the literature and other Great Lakes valuation studies, a stated preference valuation survey was developed during 2021. We purchased a sample of Great Lakes and Ontario residents from Dynata (dynata.com), a market research company that was formed by merger between Research Now and Survey Sampling International in 2017. Dynata provides opt-in survey samples for academic research. Online survey responses have been found to yield similar results to more traditional survey modes (Lindhjem and Navrud 2011).

Online surveys can use either probability-based or non-probability (i.e., opt-in, convenience) based samples of respondents. Internet surveys with opt-in panel samples are less expensive than probability-based samples and likely the least expensive of all survey modes. The drawback of opt-in panel data is that it may be of relatively low quality as some poorly compensated opt-in panel respondents pay little attention to the details of the valuation questions. Johnston et al. (2017) assert that high quality samples use probability-based sampling and the Dillman method, with repeated contacts, for internet surveys. Probability-based internet panels are more expensive but respondents may pay more attention to the surveys and may generate higher quality data.

Recently, Whitehead, et al. (2023), in a referendum question, find that opt-in survey responses don't pass validity tests while probability-based responses do in a single-bound contingent valuation survey. Giguere, Moore and Whitehead (2020) find that opt-in data does not pass validity tests when only the first question is used in the analysis but the multiple question data does. Sandstrom-Misty et al. (2021) compare two opt-in panels, MTurk and Qualtrics, with a mixed mode mail/internet sample and repeated referendum questions. They find that each sample produces valid results but there are differences in the survey responses to the program cost and scope variables across samples. Following this literature we developed our survey using repeated referendum questions and employ ANA methods when validity issues arise.

The sample is composed of households who live in the eight Great Lakes states and

Ontario. The target sample for these two regions is based on overall population. In each of the Great Lakes states the sample is stratified by coastal and non-coastal counties. Minnesota, Michigan and Wisconsin have over 50% of the state population in the coastal counties. For these states the goal was to achieve a 50/50 split in sample between coastal and non-coastal counties. The other Great Lakes states have coastal populations that range from 3% to 35% of the state population. For these we tried to achieve as much sample in the coastal counties as possible, but no more than 50%.

The target sample size for each state (within the 85% of the total sample for the U.S.) is roughly based on the midpoint of (1) the percentage of the overall sample in coastal counties and (2) the percentage of the overall sample within the states. States that might have less than a sample size of 100 in this scheme are increased to 100. The remaining state targets are reduced proportionally. The targets for the state samples were Illinois – 17%, Indiana – 7%, Michigan – 17%, Minnesota – 7%, New York – 10%, Ohio – 10%, Pennsylvania – 7%, Wisconsin – 10%. The target sample for Ontario is 15% of the total. The sample is balanced on gender and age categories at the state level.

The final survey was fielded in November 2021.[4] Respondents are initially asked about their state of residence, categorical age (e.g., between 18 and 24) and zip code. Respondents who indicated that they lived in a U.S. state other than one of the Great Lakes states or a province of Canada other than Ontario were sent to the termination page. Over 1700 Dynata panelists were Great Lakes region residents and completed the survey. In order to increase data quality, we deleted any respondent who provided an age that was not +/- one year away from 2021 minus

[4] The final survey, raw data, and data summaries can be accessed here: http://bit.ly/GLFC2022.

their birth year (which was asked at the end of the survey), provided an income category that was inconsistent with the income screener question and provided a zip code that was outside the range of state zip codes. Once these responses were deleted from the data, 1593 Great Lakes state and Ontario residents remain for the analysis. Fifteen percent of the sample is from Ontario (n=240), 16% percent of the sample is from Illinois (n=222), 8% from Indiana (n=114), 17% from Michigan (n=234), 9% from Minnesota (n=121), 10% from New York (n=138), 12% from Ohio (n=158), 11% from Pennsylvania (n=143) and 16% from Wisconsin (n=223). Forty-seven percent of the U.S. resident sample resides in coastal counties. Stratification weights are developed so that the weighted population is representative in terms of coastal and state residence.

Questionnaire

In order to enhance perceived consequentiality (Johnston et al. 2017), the introductory section of the survey begins with a statement that the study is funded by the GLFC and a list of the duties of the GLFC obtained from http://glfc.org/about. The GLFC logo is placed at the top of this page. The next page also contains the GLFC logo and describes the objective of the survey, its policy relevance and how results will be disseminated.

Respondents are then told that the Great Lakes consist of Lake Erie, Lake Huron, Lake Michigan, Lake Ontario and Lake Superior, their tributaries and connecting waters. Then respondents are asked questions about their knowledge of the Great Lakes. Thirteen percent of respondents know a lot about the Great Lakes, 35% know some, 32% know a little and 20% know nothing. Those respondents who know more than nothing about the Great Lakes are asked how much they know about Great Lakes recreational fisheries. Ten percent of respondents know a lot about the Great Lakes recreational fisheries, 32% know some, 33% know a little and 25% know nothing. Respondents who know more than nothing about the Great Lakes recreational fisheries are asked their opinion about whether Great Lakes recreational fisheries are improving, deteriorating or staying the same. Twenty-six percent of respondents say recreational fisheries are improving, 32% say deteriorating, 28% say staying the same and 15% say that they do not know.

We asked questions about recreational use of the Great Lakes. Respondents are asked if they participated in water-based recreational activities during the past 12 months. The most visited lakes are Lake Michigan (11% of the full sample), Lake Erie (10%) and Lake Superior (7%). The average number of fishing trips to each lake ranges from 4 to 5 for those who take trips. Twenty-three percent of respondents say that they have been recreational fishing in the last 12 months at any of the Great Lakes. Forty-three percent say that they have friends or family members who have fished the Great Lakes in the past year. Fifty-five percent of respondents are in neither category.

The survey next introduces a hypothetical “Great Lakes Fishery Management Plan” that would be developed by the Great Lakes states and Ontario. The first screen states that the “plan would implement policies to control aquatic invasive species, reduce industrial water pollution, reduce agricultural water pollution, restore coastal wetlands and support fisheries management activities”. Each of these policies are briefly described. Respondents are then asked if they support various government activities to implement the policies. Support for all of the policies is high. Eighty-seven percent support (“strongly support” or “somewhat support”) water quality regulations, 80% support policies to reduce aquatic invasive species, 84% support wetlands restoration and 86% support fisheries management.

This is followed by a section that describes the fish species that would be affected by the fishery management plan. These are described as warm water (perch, black bass, walleye and pike) and cold water (salmon, steelhead, lake trout and other trout) species. Respondents can click on links that take them to web pages with information about each fish from the Michigan Department of Natural Resources. Respondents are then asked how much they know about each fish. Thirteen percent, 9%, 16% and 14% of respondents know a lot about yellow perch, black bass, walleye and pike. Twenty percent, 8%, 15% and 9% know a lot about salmon, steelhead, lake trout and other trout.

The specifics of the fishery management plan are then described. First is a question that asks about support for the goal of the plan: "achieve well-balanced and productive fish populations in the Great Lakes in order to maintain the sustainable harvest of warm water and cold water species." The sustainable harvest is defined for the respondent as "the amount of fish that can be caught and kept each year without resulting in a decline in the fish population". Fifty-six percent of respondents strongly support this goal of the fishery management plan and 30% somewhat support this goal.

Respondents are told that the plan would be costly and the payment vehicle is then described as a one-time increase in state and Provincial taxes. Respondents are asked if they would support a tax increase to fund the plan. We chose a one-time payment schedule because a one-time tax increase is easier for respondents to understand and avoids complications associated with discounting future values (Howard, Whitehead and Hochard 2020). A one-time payment is likely to lead to conservative willingness to pay estimates. Twenty-eight percent of respondents would strongly support a one-time tax increase and 35% would somewhat support it. Only 16% percent of respondents do not support this payment vehicle.

Then, respondents are asked several questions that are designed to allow them to become familiar with the stated preference referendum questions. Respondents are told that bag limits and size limits would be used to reduce catch rates if the sustainable harvest could not be maintained. Sixty-five percent of respondents said that they read this instruction page very closely, 30% said they read it somewhat closely and 5% said they read it not very closely. Respondents are presented with a table to illustrate the referendum scenario: without the fishery management plan that there would be a 50% reduction in the recreational catch of, in this case, cold-water species. With the plan there would be no change in the catch. Sixty percent of respondents said that they read this instruction page very closely, 35% said they read it somewhat closely and 5% said they read it not very closely.

In order to help survey respondents understand a percentage decrease they are presented with a bar chart that shows 10%, 20%, 30%, 40% and 50% reductions in catch rates relative to 10 fish. Then we ask respondents a question about how many fish would be caught, relative to 10, if a randomly assigned percentage decrease in catch rates due to a combination of catch limits. Each respondent received one of five randomly assigned reductions: 10%, 20%, 30%, 40% and 50%. Sixty-five percent of respondents answered this question correctly.

Respondents are told that the cost of the plan is uncertain based on the decrease in recreational catch to be avoided and the number of policies and regulations used. The survey states that the one-time tax increase would range from $10 to $250.[5] The example table from the previous question is repeated with the cost amount ($100) displayed in the bottom row. Fifty-seven percent of respondents said that they read this instruction page very closely, 36% said they read it somewhat closely and 7% said they read it not very closely.

Then the referendum is described and respondents are told they will be asked for their referendum vote. Sixty-four percent of respondents said that they read this instruction page very closely, 30% said they read it somewhat closely and 6% said they read it not very closely. The pairwise correlation coefficients for each of the "closely" variables range from $r = 0.65$ to $r = 0.75$, suggesting that there is a minority of respondents who didn't read any of the instructions closely.

Following the pretest results, we focus our ex-ante hypothetical bias mitigation strategy on "cheap talk" and "honesty priming" (Howard et al. 2017). We include a short cheap talk script: "In studies like this it is often the case that more people say they would vote in favor of the policy than actually do when in a real referendum. While the voting questions are hypothetical, we ask that you answer them just like you would if there were real referendum votes." We follow this with an "oath" question. Eighty-four percent of respondents say that they will try to answer the hypothetical voting questions just like if they were real referenda.

Each stated preference question is framed as a referendum with a tradeoff between decreases in the sustainable harvest (at a cost of $0) and maintaining the current sustainable

[5] The survey was pretested with 432 U.S. Great Lakes residents in July 2021.We developed a range of cost amounts based on the pretest data.

harvest at a positive cost amount. For each type of fish (warm vs. coldwater species), there were two attributes that were varied. The size of the catch reduction, which had 5 levels (10, 20, 30, 40, 50 percent reduction in the absence of the program) and the one-time household cost, which had 7 levels ($10, 50, 90, 130, 170, 210, 250). From this, we created an efficient design of 15 choices, which we blocked into 5 blocks of 3 choices each (Figure 2). Thus, the total design consists of 30 choices (15 with reductions to warm water species and 15 with reductions to cold water species). Each respondent is presented with 6 total choices, one block with 3 choices that involve warm water species reductions and one block with 3 choices with cold water species reductions. Choice order within each block was randomized, as was which species type was presented first. Vossler, Doyon and Rondeau (2012) find that this type of repeated single bound question is incentive compatible if respondents consider each response independent of the others.

Following each scenario respondents were asked “How would you vote in this situation?” Answer categories are “I would vote in favor of the plan”, “I would vote against the plan” and “I don’t know how I would vote”. Over all of the six questions, 44% would vote in favor of the plan, 31% would vote against the plan and 25% do not know how they would vote. If respondents stated that they would vote in favor of the plan they are presented with a budget reminder and asked a follow-up certainty question that allows for an ex-post hypothetical bias mitigation approach: “How certain are you that you would actually vote in favor in this situation if it were a real referendum?” Answer categories are “very certain”, “somewhat certain” and “not certain at all.” Seventy percent of those in favor of the plan are very certain that they would actually vote in favor, 27% are somewhat certain and 3% are not certain at all. Recoding all of the responses in favor of the plan that were not very certain to no, 31% of respondents are very certain that they would vote in favor.

We then asked respondents to state how much attention they paid to each of the attributes. Fifty-seven percent of respondents paid a lot of attention to the amount of the one-time tax increase, 28% paid some attention, and 15% said they did not pay much attention to the attribute (i.e., not much, none). Thirty-one percent paid a lot of attention to the decrease in warm-water recreational fish catch, 43% paid some attention and 26% did not pay much attention. Thirty-two percent paid a lot of attention to the decrease in cold-water recreational catch, 41% paid some attention and 27% did not pay much attention.

Respondents are then asked standard stated preference debriefing questions. Eighty-four percent state that they strongly agree or somewhat agree with a statement that they understood all of the information presented to them about the hypothetical situations. Fifty-eight percent strongly or somewhat agree with the statement that they have confidence in the ability of the government to manage Great Lakes recreational fisheries. Eighty-one percent strongly or somewhat agree with the statement "I believe the results of this survey will be shared with the Great Lakes Fisheries Commission …" and 78% strongly agree or somewhat agree with the statement "I believe the results of this survey could affect decisions …". Seventy-three percent agree that the survey will be shared and will affect decisions and believe that the survey is consequential (Carson and Groves 2007, Mohr et al. 2021).

Two other debriefing questions were designed to investigate the extent of potential hypothetical bias. Eighty-nine percent of respondents "answered the hypothetical questions just like [they] would if they were real referenda" and 69% "think that my own taxes would actually increase …". Finally, we asked respondents whether they agree or disagree that "this survey is biased." Nineteen percent agree that the survey is biased, 36% neither agree nor disagree, 37%

disagree and 8% do not know.

A summary of the socioeconomic variables is presented in Table 1. Thirty-eight percent of the sample is male and the average age is 49. Forty-seven percent of the sample is married and 83% of the sample is white. The average number of years the respondent has spent in school is 14[6]. Fifty percent of respondents are currently working for pay and the mean annual household income is $62 thousand.[7] Eighty-one percent of the respondents voted in the last election, 35% are politically liberal and 31% are conservative. Twenty-three percent of respondents are Great Lakes anglers and 43% know someone who is a Great Lakes angler.

Empirical Model

The economic theory behind our estimate of willingness to pay for the total economic value of an amenity change begins with the indirect utility function, $v(c, y, q)$, where c is the cost of a fishing trip, y is income, and q is the sustainable harvest of warm and cold-water species (i.e., quality). The willingness to pay to avoid decreases in the sustainable harvest is the total economic value, TEV:

$$v(c, y - TEV, q) = v(c, y, q') \qquad (1)$$

where $q > q'$ is the quality change described by the policy. In this case, TEV is the willingness to pay to avoid reductions in recreational harvest. Total economic value includes use value, UV, and passive use values, PUV, which are those held by households who do not enjoy the resource

[6] The years schooling variable is coded as 10 if the respondent did not finish high school, 12 for high school graduates, 13 for some college but no degree, 14 for a two-year college degree, 16 for a four-year college degree, 18 for a master's degree, 19 for a professional degree and 21 for a PhD degree.
[7] The household income variable is coded at the midpoint of the interval in thousands (e.g., $35 if household income is between $30,000 and $39,999) with a top code at $175 if income is greater than $150,000.

on-site (i.e., do not take fishing trips). Each respondent is presented with a randomly assigned tax amount, t, and compares utility with and without the policy when considering their referendum votes:

$$v(c, y - t, q) \gtrless v(c, y, q') \tag{2}$$

In order to estimate TEV with a dichotomous choice regression model (e.g., logit, probit) first suppose that respondents have a linear in parameters utility function,

$$v = \alpha + \beta c + \delta y + \gamma q \tag{3}$$

The change in utility created by a policy to maintain quality level q at a cost t is

$$\Delta v = v(c, y - t, q) - v(c, y, q') \tag{4}$$

Substituting the linear utility function (3) into (4) yields

$$\Delta v = \alpha + \beta c + \delta(y - t) + \gamma q - (\alpha + \beta c + \delta y + \gamma q') \tag{5}$$

Assuming constant marginal utility across states of the world equation (5) simplifies to:

$$\Delta v = \gamma q - \delta t + \gamma q' \tag{6}$$

where $\gamma q = \theta$, is a status quo constant. The probability of a vote in favor of the policy is

$$\Pr(\Delta v \geq 0) = \Pr(\theta - \delta t + \gamma q' + e) \tag{7}$$

where e is an error term. Increases in the tax amount has a negative effect on the change in utility and the probability of a vote in favor of the policy. Increases in the sustainable harvest decrease without the policy have a positive effect on the change in utility.

Assuming the error term follows a Type 1 extreme value distribution, the probability function is operationalized with the logistic regression model:

$$\text{(8)} \qquad \Pr\,(\Delta v \geq 0) = \frac{1}{1 + \exp\,(-(\theta - \delta t + \gamma q'))}$$

We further use the equality-constrained latent class model (ECLC) to identify respondents who may have ignored the cost and quantity variables. The ECLC involves estimation of C classes of respondents, $c = 1, \ldots, C$:

$$\text{(9)} \qquad \Pr(\Delta v \geq 0 \mid c) = \frac{1}{1 + \exp\,(-(\theta_c - \delta_c t + \gamma_c q')}$$

Non-attending behavior is modeled by constraining the coefficients on cost and quantity to zero and estimate the probability that a respondent belongs to the non-attending class. All other coefficients are constrained to be equal across classes. With $k = 3$ attributes the maximum possible number of classes is $C = 2^k$ including a full preservation class (with all attributes attended to), a full non-attendance class (with the coefficients on all attributes constrained to zero), three classes with individual coefficients set to zero and three classes with two coefficients set to zero. The model with the best statistical fit, $C \leq 2^k$, is chosen as the model with the lowest AIC statistic.

With a linear functional form for utility the mean (and median) TEV estimate is the tax amount that makes the probability that the change in utility is equal to 50% (Hanemann 1984). Setting $Pr(\cdot) = 0.50$ yields the total economic value for a given change in the sustainable harvest

$$TEV = -\frac{\theta + \gamma q'}{\delta} \tag{10}$$

The standard errors of WTP are estimated with the Delta method (Cameron 1991).

Due to improved statistical fit we focus the empirical analysis on the log-linear approximation of the utility difference:

$$\Delta v = \theta - \delta lnt + \gamma lnq' \tag{11}$$

The mean total economic value is undefined in a logistic regression with this functional form. The median total economic value estimate with a log-linear utility approximation is

$$TEV = exp\left(-\left(\frac{\theta + \gamma lnq'}{\delta}\right)\right) \tag{12}$$

The log-linear model also facilitates the estimation of scope elasticity as the negative ratio of the scope and tax coefficients (Whitehead 2016),

$$\varepsilon_q = -\frac{\gamma}{\delta} \tag{13}$$

Empirical Results

The referendum vote responses by cost amount are presented in Table 2. The percentage of votes in favor is 71% at a cost of \$10 and decreases monotonically to 29% when the cost amount is \$250. Sixteen percent of respondents do not know how they would vote when the cost is \$10 and between 23% and 29% at higher cost amounts. The differences in the cell probabilities are statistically significant when the votes in favor are assessed against votes against and don't know responses ($p < 0.01$) and when don't know and against votes are combined ($p < 0.01$).

The referendum vote responses by scope amount (i.e., decreased catch) are presented in Table 3. The percentage of votes in favor is 29% when scope is 10% and increases non-monotonically to 51% when the scope amount is 50%. Those respondents who do not know how they would vote is between 24% and 28% at different scope amounts. The differences in the cell probabilities are statistically significant when the votes in favor are assessed against votes against and don't know responses ($p < 0.01$) and when don't know and against votes are combined ($p < 0.01$).

The willingness to pay logit model results are presented in Tables 4. We estimate separate coefficients for decreases in the sustainable harvest of warm-water and cold-water species even though a statistical test fails to reject equality of coefficients in all models estimated. In these models we focus exclusively on the natural log functional form since the linear scope coefficients are statistically insignificant in models that do not consider scope ANA and the log form has better overall statistical fit. We estimate population weighted models although there are very few differences from unweighted models. All models are estimated with clustered standard errors except for the latent class ANA model which internally accounts for correlation within respondents. Each of the four models in Table 4 are statistically significant according to the model chi-squared. In each of the four models the coefficients on the tax and scope variables have statistically significant expected signs. As the required tax amount increases the probability that the respondent will vote in favor falls. As the potential reduction in the sustainable harvest increases the probability that the respondent will vote in favor of the policy increases. Comparing the naïve model 1 (i.e., ignoring hypothetical bias and insensitivity to scope) and model 2 with hypothetical bias mitigated by recoding, the coefficients on the tax and scope variables are similar but the constant is 59% smaller in the hypothetical bias model. The AIC statistic in the hypothetical bias model is lower than that in the naïve model, indicating that model 2 is statistically preferred.

The inferred attribute non-attendance hypothetical bias model 3 is in the third column of Table 4. This is a latent class model with two classes of respondents with the coefficient on the tax variable constrained to be equal to zero in the non-attentive class with all of the other coefficients constrained to be equal across classes. The probability that a respondent will be in the full preservation class is 71% and there is a 29% probability that respondents will be in a class that ignores the tax amount when responding to the referendum questions. This magnitude is similar to the debriefing question where 28% of respondents stated that they paid some attention to the tax amount and 15% said they did not pay any attention to this attribute. The constant is 21% lower and 34% greater than the constants in models 1 and 2, respectively. Since the constant is an element of the numerator in the willingness to pay function, this will decrease and increase model 3 willingness to pay estimate relatives to models 1 and 2, respectively. The coefficient on the tax attribute in model 3 is significantly larger in absolute value, 39% and 47% larger, than in models 1 and 2, indicating the presence of a form of hypothetical bias. Since the coefficient on the tax amount is the denominator in the willingness to pay estimate, a tax coefficient further away from zero will decrease the willingness to pay estimate. Also, the coefficient on the tax variable significantly increases in statistical precision with the ratio of the coefficient estimate to the standard error 2.4 times larger in model 3 relative to the previous models. The coefficients on the scope variable are about 100% larger than in models 1 and 2. The AIC statistic in model 3 is lower than that in models 1 and 2, indicating that model 2 is statistically preferred.

The full inferred attribute non-attendance model 4 is in the fourth column of Table 4. This is a latent class model with two classes of respondents with the coefficients on the tax and scope variables constrained to be equal to zero in various non-attentive classes with all of the other coefficients constrained to be equal across classes. The model that minimized the AIC statistic includes four classes: full preservation, a class with ANA on the tax amount, a class with ANA on both warm-water and cold-water fishery harvest reduction attributes (i.e., scope) and a class with full non-attendance. The probability that a respondent will be in the full preservation class is 44%. The probability that respondents will be in the non-attending tax, scope and full non-attending classes is 14%, 31% and 11% implying the probability that respondents will ignore the tax amount is 25% and the probability that respondents will ignore the scope amounts is 42%. The latter magnitude is similar to the debriefing question where 43% of respondents stated that they paid some attention to the scope amounts and 26% said they did not pay any attention to this attribute.

In both tax and scope cases, the inferred ANA probability is greater than the proportion of respondents who admitted they did not pay any attention to the attribute but less than the sum of those who said they paid no attention and some attention. The coefficient on the tax attribute is significantly larger in absolute value, 79%, 89% and 29%, relative to those in models 1, 2, and 3 indicating the presence of a form of hypothetical bias (even relative to the ANA hypothetical bias model). The coefficients on the scope variables are about 7-8 times larger than in models 1 and 2 and 3-4 times larger relative to model 3. This indicates that the data exhibits a form of insensitivity to scope. This result has implications for the measure of scope elasticity below. Also, the coefficients on the scope variables significantly increase in statistical precision. The AIC statistic in model 4 is lower than in all other models, indicating that model 4 is statistically preferred.

The median willingness to pay estimates are presented in Table 5. In these models we constrain the warm and cold-water species coefficients to be equal (this is supported statistically by a likelihood ratio test) so that the willingness to pay estimates are the same for both species. In the naïve model, willingness to pay ranges from $55 per household to $74 as the harvest reduction increases from 10% to 50%. In the re-coded hypothetical bias model, the willingness to pay estimates are 73% lower, ranging from $15 per household to $20 as the harvest reduction increases from 10% to 50%. The willingness to pay estimates from the ANA hypothetical bias model are higher but very similar to those in the recoded model, ranging from 2% to 17% higher as the harvest reductions increase from 10% to 50%. The logit coefficients in Model 4 in Table 4 are substantially different from the other models which leads to substantially different willingness to pay estimates. In the full ANA model, willingness to pay ranges from $33 to $112 as the harvest reduction increases from 10% to 50%. Overall, the willingness to pay estimates are higher than in the naïve model even after accounting for hypothetical bias, though a full accounting of the differences reveals that, relative to the naïve model, the full ANA model produces lower welfare estimates at low harvest reduction values and higher welfare estimates at high harvest reduction values. This is because the impact of the higher scope coefficients in the numerator of the willingness to pay function is greater than the higher (in absolute value) tax amount coefficient in the denominator. Of course, the full ANA model willingness to pay estimates are driven by less than 100% of the survey respondents. This fact will be accounted for when willingness to pay is aggregated over the population of households who reside in Great Lakes U.S. states and Ontario.

Scope elasticity is the percentage change in willingness to pay divided by the percentage change in scope. The scope elasticity estimates range from 0.18 in the naïve model to 0.77 in the ANA model that accounts for hypothetical bias and scope insensitivity. Scope elasticities can range from 0 to 1 so these magnitudes suggest that the results are plausible in each model (Whitehead 2016). The differences in willingness to pay and the sensitivity of willingness to pay to the scope of the proposed policy can be seen in Figure 1. The two hypothetical bias models produce similarly low willingness to pay estimates with modest increases over the policy range. The naïve and full ANA model produces willingness to pay estimates of similar, higher magnitude but the ANA model that accounts for hypothetical bias and sensitivity to scope is more steeply sloped and better exhibits predictions from economic theory (i.e., more is better). The scope elasticity from the full ANA model is estimated precisely with a 95% confidence interval of 0.69, 0.85.

Aggregate benefits

Median willingness to pay estimates can be aggregated over the populations of the Great Lakes states and Ontario to estimate the aggregate benefit of avoiding reductions in sustainable recreational harvest. Since the tax payment is one-time, relative to annual, the aggregate benefit estimates should be considered the present value of annual benefits in perpetuity. It is more appropriate to use mean willingness to pay estimates in benefit-cost analysis. The median willingness to pay is the amount that 50% of respondents would pay. It is the amount that would lead to a 50/50 vote in an actual referendum. The mean willingness to pay is typically greater than the median since the willingness to pay distribution has a long upper tail. In simple linear models (without scope variables included), we find that the mean willingness to pay from the linear model is 55% greater than the median willingness to pay. Therefore, the aggregate benefit estimate below should be considered conservative.

We use the model 4 full ANA willingness to pay estimates for the aggregate benefit estimates. This is for two reasons. First, the model is statistically superior to the other three models. Second, model 4 produces willingness to pay estimates that are highly sensitive to the scope of the policy while also mitigating hypothetical bias. These willingness to pay estimates are the highest from Table 5 but lower than the naïve estimates at low levels of the harvest reduction variable.

That said, it is not straightforward how one should aggregate willingness to pay estimates from an equality constrained latent class model with ANA constraints over the population. One approach is to assume the those who ignore cost and scope attributes have the same willingness to pay as respondents who pay attention to all of the attributes in the survey. The assumption here would be that non-attentive survey respondents are similar to attentive survey respondents in terms of their willingness to pay and would reveal as much in their referendum votes if they were properly incentivized to consider the attributes in the referendum voting scenarios. But, without evidence to that effect we risk overstating the aggregate benefits with this assumption. Instead we estimate aggregate benefits assuming that the correlation in how attentive respondents are to the attributes in the hypothetical scenarios is positively correlated with how accurate their referendum votes are to their true willingness to pay values. We aggregate these household level estimates over the number of households in each state and Ontario with an adjustment for the estimated proportion of households who considered the attributes. The lower bound aggregate benefit estimate includes the full preservation proportion of respondents, those who are estimated to attend to all of the attributes. The upper bound aggregate benefit includes those respondents who attended to at least one of the attributes.

The aggregate benefit estimates are presented in Table 7. For the U.S. Great Lakes states, the lower bound aggregate benefit estimate is $1.20 billion to avoid a 10% reduction in sustainable recreational harvest and increases to $4.26 billion to avoid a 50% reduction with the lower bound assumption. We use the November 30, 2021 U.S.-Canada exchange rate to convert Canadian dollars to U.S. dollars (one U.S. dollar is equivalent to 1.2782 Canadian dollars). The aggregate benefit estimate is $209 million to avoid a 10% reduction in sustainable recreational harvest to Ontario households and rises to $723 million to avoid a 50% reduction. With the upper bound assumption, the aggregate benefit to U.S. Great Lakes households is $2.45 billion to avoid a 10% reduction and rises $8.45 billion to avoid a 50% reduction in sustainable catch. The aggregate benefit to Ontario households rises from $426 million to $1.47 billion to avoid 10% to 50% catch reductions.

These estimates can be compared to those from naïve WTP model to gain insights into using ANA models, and their aggregation implications, in benefit cost analysis. Considering the lower bound aggregate benefit estimate, the WTP estimate from the naïve model aggregated over the entire population is 3.86 times greater than that in Table 7 at the 10% reduction level. This difference decreases to 1.5 times higher for the naïve model when the harvest reduction is 50%. Considering the upper bound estimate, the WTP estimate from the naïve model 1.9 times greater than that in Table 7 at the 10% reduction level. The estimates are almost equal at the 30% reduction level and the naive aggregate benefit estimate is 1.36 times higher than that from the ANA model when the harvest reduction is 50%.

Conclusions

The purpose of this study is to estimate the total economic value held by the U.S. and Canadian publics for Great Lakes fisheries, including values held by recreational anglers and others. Having well-balanced and productive fish populations are important for supporting recreational fisheries in the Great Lakes where each year almost 1.4 million anglers fish. There are a number of environmental stressors that threaten the sustainable recreational harvest of these species. Fishery managers cooperatively manage fisheries in the Great Lakes by stocking predator fishes, regulating harvest and enforcing of fishing regulations. We have employed a repeated referendum stated preference question to estimate the value of avoiding recreational harvest reductions for Great Lakes fisheries.

We find that survey respondents are willing to pay higher taxes to avoid reductions in recreational catch. The one-time median willingness to pay ranges from $32 to $112 to avoid 10% to 50% catch reductions in our best statistical model. We investigate two methodological issues: hypothetical bias and insensitivity to scope. To mitigate hypothetical bias, we include a short cheap talk statement, an oath question and ask respondents who indicated that they are willing to pay for the policy how certain they are about their referendum response. We compare the willingness to pay estimates from the model with responses where uncertain “in favor” votes are recoded to “against” votes to an attribute non-attendance model that focuses on the policy cost attribute. We find that the two hypothetical bias approaches yield similar results. We estimate another attribute non-attendance model with consideration of the scope of the policy and find that the scope elasticity is significantly underestimated, 2 to 3 times, in the other models. The willingness to pay in this last, statistically preferred, model is overall higher than in each of the other models.

The aggregate benefit of avoiding catch reductions to households in the Great Lakes states and Ontario is substantial with the lower bound estimates ranging from $1.2 billion to $4.2 billion to avoid 10% to 50% reductions in sustainable harvest, respectively. In comparison, naïve model WTP estimates aggregated over the entire population produce much higher aggregate values, 3.86 to 1.5 times higher as the harvest reductions range from 10% to 50%. Considering upper bound estimates, the naïve model produces higher aggregate benefit estimates at the 10% and 20% harvest reductions and lower aggregate benefit estimates at the 40% and 50% reductions.

In terms of future research, we need more comparisons between certainty recoding and attribute non-attendance hypothetical bias models to determine if these results are robust across different valuation scenarios and contexts. Similarly, more studies should consider attribute non-attendance as a factor that affects insensitivity to the scope of the policy. There are few barriers to these comparisons as there are many studies that ask willingness to pay certainty follow up questions and present respondents with more than one valuation scenario, which is a necessary condition for estimation of a latent class model. We use the equality constrained latent class model, only one form of the suite of inferred attribute non-attendance models. Future research could consider these comparisons with other inferred ANA models and also stated ANA models. Also, more research is needed to consider the appropriate strategy to developing aggregate benefit estimates in an attribute non-attendance model. Our approach is to make aggregation rule assumptions based on attribute non-attendance and willingness to pay. The different assumptions lead to a range of aggregate benefit estimates. In our example, we find that this has significant implications for aggregate benefits and, therefore, benefit cost analysis, but more research is needed before we can conclude that naïve models lead to biased aggregate benefit estimates.

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Table 1. Descriptive statistics						
Variable	Label	Mean	SD	Min	Max	Sample size
Male	1 if male gender, 0 otherwise	0.38	0.48	0	1	1593
Age	age in years	49.39	18.86	18	91	1593
Married	1 if married, 0 otherwise	0.47	0.50	0	1	1558
White	1 if white, 0 otherwise	0.83	0.38	0	1	1565
School	years schooling	14.22	2.27	10	21	1580
Working	1 if working, 0 otherwise	0.50	0.50	0	1	1549
Income	household income in 2020 before taxes (midpoint $1000)	61.99	45.39	5	175	1504
Vote	1 if voted in last election, 0 otherwise	0.81	0.39	0	1	1557
Liberal	1 if politically liberal, 0 otherwise	0.35	0.48	0	1	1558
Conservative	1 if politically conservative, 0 otherwise	0.31	0.46	0	1	1558
Angler	1 if is a Great Lakes Angler	0.23	0.42	0	1	1593
Know	1 if knows a Great Lakes Angler	0.43	0.50	0	1	1593

Table 2. Referendum votes by the cost amount					
Cost	Against	I don't know	In Favor	Total	% In Favor
$10	158	199	882	1239	71.19
$50	250	290	739	1279	57.78
$90	310	333	634	1277	49.65
$130	429	332	568	1329	42.74
$170	481	378	430	1289	33.36
$210	514	334	390	1238	31.50
$250	819	529	559	1907	29.31
Total	2961	2395	4202	9558	43.96
Note: Sample size is 1593 respondents × 6 votes per respondent					

Table 3. Referendum votes by the scope amount					
Scope	Against	I don't know	In Favor	Total	% In Favor
10% reduction	552	364	373	1289	28.94
20% reduction	548	454	895	1897	47.18
30% reduction	592	445	820	1857	44.16
40% reduction	608	523	816	1947	41.91
50% reduction	661	609	1298	2568	50.55
Total	2961	2395	4202	9558	43.96
Note: Sample size is 1593 respondents × 6 votes per respondent					

Table 4. Willingness to pay logit models: dependent variable is Vote (in favor = 1, 0 otherwise)

	Model 1: Naïve			Model 2: Ex-post, Hypothetical Bias			Model 3: ANA, Hypothetical Bias			Model 4: ANA, Hypothetical Bias and Scope		
	Coeff.	SE	t-stat	Coeff.	SE	t-stat	Coeff.	SE	t-stat	Coeff.	SE	t-stat
Constant	1.893	0.186	10.20	1.114	0.173	6.44	1.494	0.22	6.74	1.625	0.23	7.00
LN(Tax)	-0.528	0.028	-18.97	-0.499	0.026	-18.95	-0.732	0.02	-45.94	-0.944	0.03	-31.00
LN(Warm)	0.090	0.035	2.57	0.093	0.034	2.75	0.203	0.06	3.61	0.713	0.04	16.52
LN(Cold)	0.103	0.035	2.97	0.106	0.034	3.15	0.218	0.06	3.89	0.737	0.04	17.67
							Class probabilities					
Full Preservation							0.709	0.01	51.62	0.437	0.02	18.52
Tax ANA							0.291	0.01	21.18	0.140	0.02	7.64
Scope ANA										0.312	0.03	9.47
Full ANA										0.111	0.02	5.87
AIC	12,487.6			11,242.0			10,371.7			10,002.8		
Pseudo R^2	0.051			0.050			0.170			0.200		

Note: The sample size is 9558 in each model with 1593 cross-sections and 6 time-periods

Table 5. Median household willingness to pay to avoid recreational catch reductions

	Model 1: Naïve			Model 2: Ex-post, Hypothetical Bias			Model 3: ANA, Hypothetical Bias			Model 4: ANA, Hypothetical Bias and Scope		
	WTP	SE	t-value	WTP	SE	t-value	WTP	SE	t-value	WTP	SE	t-value
10% Reduction	54.80	5.65	9.70	14.70	2.09	7.02	14.94	1.77	8.42	32.50	5.11	6.36
20% Reduction	62.25	4.82	12.91	16.89	1.98	8.55	18.27	1.43	12.75	55.59	7.57	7.34
30% Reduction	66.98	4.89	13.69	18.30	2.00	9.13	20.51	1.33	15.43	75.65	9.52	7.95
40% Reduction	70.64	5.36	13.19	19.39	2.10	9.23	22.30	1.41	15.85	94.59	11.27	8.39
50% Reduction	73.55	5.97	12.33	20.27	2.23	9.10	23.77	1.59	14.93	112.14	12.88	8.71

Table 6. Scope elasticity			
Model	Elasticity	SE	t-value
Naïve	0.18	0.07	2.72
Ex-post: Hypothetical Bias	0.20	0.07	2.89
ANA: Hypothetical Bias	0.29	0.08	3.73
ANA: Hypothetical Bias and Scope	0.77	0.04	17.89

Table 7. Range of aggregate benefit estimates of avoiding recreational catch reductions implied by attribute non-attendance models: Mean and 95% confidence interval ($US2021, millions)

	Lower Bound					
	Great Lakes U.S. States			Ontario		
	Mean	LB	UB	Mean	LB	UB
10% Reduction	1204	833	1575	209	145	274
20% Reduction	2060	1510	2610	358	263	454
30% Reduction	2803	2112	3494	487	367	608
40% Reduction	3505	2686	4324	609	467	752
50% Reduction	4155	3220	5091	723	560	885
	Upper Bound					
	Great Lakes U.S. States			Ontario		
	Mean	LB	UB	Mean	LB	UB
10% Reduction	2450	1694	3205	426	295	557
20% Reduction	4191	3072	5310	729	534	923
30% Reduction	5703	4297	7109	992	747	1236
40% Reduction	7130	5464	8796	1240	950	1530
50% Reduction	8454	6551	10,356	1470	1139	1801

Note: The lower bound includes those who the 43.7% of respondents who sort into the full preservation class of the fourth model in Table 4. The upper bound excludes the 11.1% of respondents who sort into the full non-attendance class of the fourth model in Table 4.

Figure 1. Willingness to pay functions