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Abstract

In 2011, Lake Erie experienced a record-setting harmful algal bloom (HAB), posing significant risks to ecosystem services, including its $1.5 billion sport fishing industry. Using a mail survey of 3,000 Ohio recreational anglers and a choice experiment, this article provides the first empirical evidence in the US to link HABs to damages to Great Lakes recreational anglers. We account for the heterogeneity in anglers' preferences using various discrete choice models, including random parameters logit, latent class model, scaled logit, and generalized multinomial logit models. The results suggest that some anglers have stronger preferences for reducing the impacts of HABs on water quality, and it is likely important to account for these differences when measuring welfare effects. Across the range of individuals in our sample, anglers are willing to pay $8–$11 more per trip for one less mile of boating through HABs enroute to a fishing site, and $6–$73 per trip more for one less hour to catch a walleye.

Keywords: Lake Erie, choice experiment, harmful algal bloom, recreational angler, non-market valuation, water quality

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Excessive nutrient runoff from agricultural production contributes to an increasing incidence of freshwater eutrophication and coastal hypoxia in the United States and worldwide (Diaz and Rosenberg 2008), posing great risks to the sustainability of many freshwater and marine ecosystems, including the Great Lakes region, the Gulf of Mexico, the Baltic Sea in Europe, and Lake Taihu in China. In 2011, the western basin of Lake Erie experienced a harmful algal bloom (HAB) of unprecedented size and severity (Michalak et al. 2013), which severely compromised multiple ecosystem services provided by the lake, including recreation opportunities, public health, and safe drinking water. In particular, dubbed as the Walleye Capital of the World, Lake Erie is the home to a $1.5 billion sport fishing industry for over 2 million anglers, and what is considered world class walleye and small bass fisheries (Lucente et al. 2012). Scientific studies have shown that HABs could lead to fish kills and pose a threat to the fishery industry by depleting dissolved oxygen and creating hypoxic dead zones through excessive algal growth (Diaz and Rosenberg 2008; Rucinski et al. 2010). However, as far as we know, there is a lack of empirical evidence that links HABs to the economic damages to the recreational fishery industry in the United States.

A large body of previous literature has been devoted to the economic valuation of benefits resulting from water quality improvements, including both revealed preference and stated preference methods (Egan et al. 2009; Fenichel, Abbott, and Huang 2013; Hynes, Tinch, and Hanley 2013; Kosenius 2010: Phaneuf and Smith 2005; Van Houtven et al. 2014; Viscusi, Huber, and Bell 2008; Whitehead et al. 2010). In particular, there is a rich literature of non-market valuation studies to estimate individuals’ willingness to pay for fishing trips and for changes in fishing site characteristics in the Great Lakes region (Bogue 2001; Lupi, Hoehn, and Christie 2003; Melstrom and Lupi 2013; Provencher and Bishop 1997) as well as for Lake Erie in particular (Hushak, Winslow, and Dutta 1988; Kelch et al. 2006). One limitation of these previous studies is that they do not explicitly link the recent occurrences of HABs with changes in water quality characteristics in Lake Erie fishing sites. One recent unpublished report indicates that the number of fishing trips to Lake Erie has declined in recent years due to rising algal toxin levels (Weicksel and Lupi 2013); however, this relies on yearly aggregate summary statistics and is descriptive in nature. Recently, Palm-Forster et al. (2016) estimated the welfare losses from simulated HAB-induced Lake Erie beach closures using benefit transfer.

In addition, most studies focusing on the Great Lakes used revealed preference techniques, such as the travel cost model. Fewer stated preference methods have been employed for valuing water quality changes in the Great Lakes, although they are widely used elsewhere. Choice experiments, for instance, are becoming increasingly popular in various fields of economics, including marketing research (Keane and Wasi 2013), health economics (Hole 2008), and non-market valuation of environmental changes (Kosenius 2010). One advantage of choice experiments over the contingent valuation method is that choice experiments can be used to identify marginal rates of substitution between different characteristics of an environmental change. This is especially important for valuing environmental goods and services that often possess complex, diverse dimensions and values (Phaneuf 2013). The study that is closest to ours in spirit is that by Kosenius (2010), who uses a choice experiment to examine willingness to pay of the

Finnish public for nutrient-reductions in the Gulf of Finland. Our study differs with Kosenius (2010) in that we focus on the US, and specifically Lake Erie, and by focusing on anglers, a population particularly exposed to HAB impacts.

The objective of this article is to assess Lake Erie recreational anglers' willingness to pay for water quality improvements and, for the first time in the US, quantify the economic impacts of HABs on Lake Erie's sport fishing industry. We hypothesize that Lake Erie recreational anglers have a considerable willingness to pay for a reduction of HABs in Lake Erie due to agricultural nutrient runoff abatement. Because HABs are a relatively recent phenomena and their impacts vary across space and time, both within years and across years, we hypothesize that there is substantial heterogeneity across individual preferences. This variation can introduce significant uncertainty in the anglers' fishing experience. Previous studies have shown that recreational anglers differ in preferred species, preferred fishing site characteristics, as well as the non-catch components of the fishing experience (see for example, Bergstrom and Cordell 1991; Rosenberger and Loomis 2001; Melstrom and Lupi 2013). We posit that more frequent and intense HABs, which occurred in both the western and central basins in recent years, added another dimension of complexity and uncertainty for the fishing experience, and that angler responses are likely to be heterogeneous. We investigate these anglers' heterogeneous preferences through a mail survey of 3,000 Ohio recreational anglers in 2014. In order to assess preferences, we employ a choice experiment with varying water quality characteristics at Lake Erie fishing sites. Specifically, respondents were asked to choose their favorite hypothetical fishing site, as characterized by walleye catch rates, miles of HAB to boat through en route to the fishing site, water clarity, time in boat getting to the fishing site, and distance from house to the boat ramp.

Using multiple discrete choice models, we estimate the anglers' demand for improvements in water clarity, increases in catch rates for walleye, and reduction in the size and intensity of HABs. The models we estimate are a conditional logit model (CL), a random parameters logit model (RPL), a latent class model (LCM), a scaled multinomial logit (SNL), as well as a generalized multinomial logit (G-MNL) model that combines the features of RPL and SNL. One common problem of the traditional CL model is that it has restrictive substitution patterns due to the Irrelevance of Independent Alternative (IIA) assumption. RPL, LCM, SNL, and G-MNL are used to uncover the heterogeneous preferences among Ohio recreational anglers for water quality improvements. We assume this heterogeneity is derived from spatial and temporal variability in the presence and intensity of HABs, and their impact on two important components of fishing trips—the fish-catching itself, and the pleasure of the trip en route to and at the specific fishing site. In Lake Erie, many fishing trips involve relatively long runs across water to arrive at the actual fishing location, and these trips may be heavily affected by HABs, even if the fishing itself is not (and vice-versa). The models we estimated differ in how they introduce the heterogeneity: RPL and LCM accounts for unobserved taste heterogeneity by allowing for continuous or discrete random coefficients for observed variables, SNL allows for scale heterogeneity, which captures the randomness of the decision-making process via a general scaling up or down of the entire vector of attribute weights (Keane and Wasi 2013), while G-MNL incorporates both scale heterogeneity and a random coefficient vector (Fiebig et al. 2010).

We find substantial willingness to pay for water quality improvements in Lake Erie: individual anglers are willing to pay \$8–\$11 per trip for one less mile of HAB needed to boat through before reaching the desired fishing site, and they are willing to pay \$6–\$73 per trip for one less hour needed to catch one more walleye. Our results also reveal that although average willingness to pay for various attributes across the models does not vary greatly, there is a wide range of values for water quality improvements among the respondents. For instance, the latent class model shows the willingness to pay for water clarity improvements from somewhat or very murky to very clear ranges from \$47 for 30% of anglers to more than \$120 for another 20% of anglers. These differences are important to capture explicitly in the estimation, particularly for welfare analysis of policies that target improvements in multiple water quality outcomes. In particular, we examine the welfare effects across three different size nutrient reduction policies. We find that due to the presence of these subsets of high-valuation anglers, approaches that do not account for heterogeneity may over-estimate the benefits. In addition, small changes in nutrient runoff would only induce minor water quality improvements, which may not provide significant benefits even for high-valuation anglers.

This article makes at least two contributions to the literature of non-market valuation of ecosystem services. First, to our knowledge, we provide the first empirical evidence that links HABs and excessive agricultural pollution in the Lake Erie watershed to significant losses in ecosystem services as shown by economic damages to a multi-billion dollar recreational fishing industry. Second, using a choice experiment and various new discrete choice models including LCM and G-MNL-II, we demonstrate the importance of accounting for individual anglers' heterogeneous preferences for water quality improvements. We find that the substantial variations in the spatial and temporal intensity of HABs in Lake Erie created additional complexity and uncertainty in the fishing trips, and led to heterogeneous behavioral responses of anglers and their willingness to pay for water quality characteristics, especially improvements in water clarity.

The remainder of the article is organized as follows: we first describe the estimation methodology, followed by the description of the data and survey design. We then present the results of the discrete choice models, which include the estimation of the welfare measures associated with various nutrient management policies. Finally, we discuss some of the implications of the models and conclude.

Methodology

The Random Utility Model (RUM) has become the standard statistical economic framework in models of recreational demand (McFadden 1974). In a choice experiment setting, respondents are asked to choose among alternative recreational destinations or policy options that are characterized by various attributes. The RUM posits that an individual chooses the alternative that yields the highest expected utility among a number of alternatives on any given choice occasion. Assume that recreational angler i has J possible multiattribute fishing sites from which to choose in the choice experiment setting, the utility U_{ijt} that angler i derives from alternative j in choice situation t is given by

$$(1) \qquad U_{ijt} = V_{ijt} + \varepsilon_{ijt},$$

where V_{ijt} is the observable indirect utility from visiting fishing site j, and ε_{ijt} is the error term which captures the unobserved, stochastic element of the utility. The conditional logit model (CL) has been the most widely used discrete choice model in recreation demand studies. With a CL model, utility can be represented by

$$(2) \qquad U_{ijt} = \beta' \mathrm{X}_{\mathrm{ijt}} + \varepsilon_{ijt}.$$

Here, $\mathrm{X}_{\mathrm{ijt}}$ is a vector of perceived site attributes including travel cost, and β is the corresponding coefficients for these attributes, while the error term ε_{ijt} is independently and identically drawn from a type-I extreme value distribution.

As shown in equation (2), CL assumes the equality of the utility functions across the respondents, and thus results in homogenous taste parameter estimates. However, previous studies have shown heterogeneity is a defining feature of nonmarket valuation (Phaneuf 2013), due to both multiple observed and unobserved factors driving recreation demand and heterogeneous individual characteristics and preferences. In addition, the estimation of only average preferences, as in CL—or misspecification of the taste distribution more generally—may lead to biased welfare analysis and wrong representation of the value of recreation sites with particular attributes that appeal to a subset of the population (Fiebig et al. 2010).

In recent years, discrete choice modelers have accounted for the unobserved heterogeneity in tastes and preferences with several additional approaches. Currently, the two most popular approaches in empirical applications are random parameters logit (RPL) model and latent class model (LCM). Both of these models allow for individual preference variations, thereby relaxing the IIA property. These approaches, however, have differing distributional assumptions. RPL allows for individual-specific, random coefficients on observed attributes and assumes a continuous distribution for individuals' preferences:

$$(3) \qquad U_{ijt} = \beta_i{}'\mathrm{X}_{\mathrm{ijt}} + \varepsilon_{ijt} = (\beta + \eta_i)'\mathrm{X}_{\mathrm{ijt}} + \varepsilon_{ijt}.$$

As shown in equation (3), β is the vector of mean attribute utility weights in the population, while η_i is the angler i's specific deviation from the mean. Theoretically, the mixing distribution for β_i in the RPL model can be anything, but it is commonly specified as multivariate normal. LCM, on the other hand, models the parameter heterogeneity across individuals with a discrete distribution which is a function of individual characteristics. The respondents are grouped into a few (K as in equation (4)) "discrete" segments or classes which remain latent for the researcher. Within each class k, the preference are homogenous (Greene and Hensher 2003):

$$(4) \qquad U_{ijt} = \beta_k{}'\mathbf{X}_{\mathbf{ijt}} + \varepsilon_{ijt} \qquad i \epsilon k, \quad k = 1, 2..K$$

Most recently, several researchers such as Louviere, Hensher, and Swait (2000) argue that the taste heterogeneity in most choice contexts can be better described as "scale" heterogeneity—meaning that for some anglers, the scale of the idiosyncratic error term is greater than for others. To better understand what scale heterogeneity means, let's rewrite the simple CL model in equation (1) with the scale of the error term, σ, made explicit instead of being normalized to one:

$$\text{(2a)} \qquad U_{ijt} = \beta' \mathrm{X}_{\mathrm{ijt}} + \varepsilon_{ijt}/\sigma.$$

The scale heterogeneity logit (S-MNL) model assumes that σ is heterogeneous in the population and hence denotes the value for angler i by the scalar random variable σ_i, we thus obtain:

$$\text{(5a)} \qquad U_{ijt} = \beta' \mathrm{X}_{\mathrm{ijt}} + \varepsilon_{ijt}/\sigma_i.$$

In (5a), all heterogeneity is in the variance of the error term while the β vector is homogenous. However, heterogeneity in scale is observationally equivalent to a certain type of heterogeneity in utility weights (Keane and Wasi 2013). Multiply (5a) by the random scale variable σ_i we obtain equation (5b), which can be interpreted as a RPL model with $\beta_i = \sigma_i * \beta$. As a result, heterogeneity in S-MNL takes the form of the vector of utility weights and β is scaled up or down proportionally across the respondents by the scaling factor σ_i.

$$\text{(5b)} \qquad U_{ijt} = \beta_i' \mathrm{X}_{\mathrm{ijt}} + \varepsilon_{ijt} = (\sigma_i * \beta)' \mathrm{X}_{\mathrm{ijt}} + \varepsilon_{ijt}$$

While the S-MNL provides an alternative way of introducing taste heterogeneity compared to RPL with normal mixing or LCM, the scaling factor σ_i in S-MNL has to be positive for all individuals and is commonly assumed to follow an exponential distribution. As a result, the vector of random coefficients β_i for all respondents must have the same sign, which is not imposed in the RPL model. Depending on whether the coefficient for the price is adjusted by the scaling factor or not, S-MNL could have S-MNL with and without price or travel cost scaled. More recently, efforts have been made to develop a model that nest S-MNL and RPL with normal mixing. Specifically, (Fiebig et al. 2010) developed a model called the generalized multinomial logit (G-MNL) model, which models the heterogeneity distribution as a continuous mixture of scaled normal. The normal mixing RPL and S-MNL are both special cases of G-MNL model (Keane and Wasi 2013). The general form of G-MNL model is given by

$$(6) \qquad U_{ijt} = \beta_i{}'\mathrm{X_{ijt}} + \varepsilon_{ijt} = [\sigma_i\beta + \gamma\eta_i + (1-\gamma)\sigma_i\eta_i]'\mathrm{X_{ijt}} + \varepsilon_{ijt},$$

where the parameter γ determines how the standard deviation of the random coefficients is scaled: in particular, when $\gamma = 0$, we obtain a model called G-MNL-II in which the standard deviations of the random coefficients η_i are scaled proportionally to their mean attribute weights. In this article, we employ this specific model, G-MNL-II, which starts with normal mixing RPL and multiplies through σ_i:

$$(7) \qquad U_{ijt} = \beta_i{}'\mathrm{X_{ijt}} + \varepsilon_{ijt} = [\sigma_i(\beta + \eta_i)]'\mathrm{X_{ijt}} + \varepsilon_{ijt}.$$

In the choice experiment setting, each individual i makes a sequence of T choices. The unconditional probability of an angler i choosing site j in the sequence of choice scenarios can be represented by

$$(8) \qquad P_{ij} = \int \prod_{t=1}^{T} L_t(j|\beta_i) f(b,\Omega) d\beta_i$$

$$= \int \prod_{t=1}^{T} \frac{\mathrm{e}^{V_{ijt}}}{\sum_{j=1}^{J} \mathrm{e}^{V_{ijt}}} f(b,\Omega) d\beta_i = \int \prod_{t=1}^{T} \frac{\mathrm{e}^{\beta_i{}'\mathrm{X_{ijt}}}}{\sum_{j=1}^{J} \mathrm{e}^{\beta_i{}'\mathrm{X_{ijt}}}} f(b,\Omega) d\beta_i.$$

In this formulation, $L_t(j|\beta_i)$ is the familiar logit probability that captures the conditional probability of choosing site j in choice scenario t, and $f(\beta, \Omega)$ is the density distribution with mean b and variance-covariance matrix parameters Ω to be estimated from the data. V_{ijt} denotes the observed utility of choosing site j in choice scenario t, and the last equality follows from the standard assumption of the utility being linear in attributes. The density $f(\beta, \Omega)$ can be specified to be discrete as in LCM or continuous in β as in any other aforementioned models.

For CL, RPL, S-MNL and G-MNL, the welfare changes for individual i from an attribute change from X_i^0 to X_i^1 and conditional on individual taste β_i, measured by compensating variation, follows the standard utility difference expression (Hynes, Tinch, and Hanley 2013):

$$(9) \qquad CV_i = -\frac{1}{\widehat{\beta_{ip}}}\left[\ln\left(\sum e^{V_i^1}\right) - \ln\left(\sum e^{V_i^0}\right)\right] = -\frac{1}{\widehat{\beta_{ip}}}\left[\ln\left(\sum e^{\widehat{\beta_i}' X_i^1}\right) - \ln\left(\sum e^{\widehat{\beta_i}' X_i^0}\right)\right],$$

where $\widehat{\beta_{ip}}$ is the parameter estimate of travel cost, $\widehat{\beta_i}$ is the vector of estimated random parameters for angler i, while V_i^1 and V_i^0 are the utility evaluated in the policy case and in the business-as-usual case. The parameter vector $\widehat{\beta_i}$ is uniform across individuals for the CL model, and varies across individuals for RPL, S-MNL, and G-MNL-II models and should be calculated following equations (3), (5b), and (7) respectively. For example, $\widehat{\beta_i} = \widehat{\sigma_i} * \hat{\beta}$ for S-MNL. For RPL, S-MNL and G-MNL models, the compensating variation measures have to be approximated by simulation from draws of the estimated distributions for the random parameters (see Train 2009 for simulation methods). For

LCM with K classes, the welfare measures have to be weighted by the predicted class membership probabilities:

$$(10) \qquad CV_i = \sum_{k=1}^{K} \widehat{\pi_{ik}} \left\{ -\frac{1}{\widehat{\beta_{ip}}} \left[\ln\left(\sum e^{V_i^1}\right) - \ln\left(\sum e^{V_i^0}\right) \right] \right\}$$

$$= \sum_{k=1}^{K} \widehat{\pi_{ik}} \{ -\frac{1}{\widehat{\beta_{ip}}} \left[\ln\left(\sum e^{\widehat{\beta_i}' X_i^1}\right) - \ln\left(\sum e^{\widehat{\beta_i}' X_i^0}\right) \right] \},$$

where $\widehat{\pi_{ik}}$ is the estimated posterior probability the angler i of being assigned to class k (Boxall and Adamowicz 2002). In this article, RPL and LCM are estimated using mixlogit (Hole 2007) and lclogit packages (Pacifico and Yoo 2012) in Stata 13, respectively, while S-MNL and G-MNL are estimated using gmnl package (Gu et al. 2013) in Stata 13.

Data and Survey Design

Following Dillman's Tailored Survey Design framework (Dillman, Smyth, and Christian 2009), we conducted a general mail survey on Ohio anglers' 2013 sport-fishing daytrips in spring 2014. Questionnaires were mailed to a sample of recent Ohio fishing license holders from 2011–2013 drawn from the Fishing License & Permit Sales database of the Ohio Department of Natural Resources (ODNR). The sample was screened to include only anglers that were 18 years of age or older, and those who purchased fishing licenses in the previous three years. We employed a stratified random sampling method, in which we oversample anglers from counties close to Lake Erie.

Specifically, 2,500 anglers were drawn from counties alongside or close to the western or central basin of Lake Erie,[i] while another 500 anglers were chosen from all other counties in Ohio. The number of sampled anglers from each county is proportional to the share of anglers from this county in the fishing license database. After pilot-testing the survey design with 16 separately randomly selected anglers, we mailed two rounds of survey packets to these 3,000 sampled anglers in mid-January, 2014 and early-March, 2014. A final reminder card was sent out late-March, 2014. We broke the sample into three subsamples and employed three different modes of incentives for each subsample: for the first 1,000 anglers, a $1 bill was included in the first round of mailings. For the other 2,000 anglers, a name card is included in the survey packet and each respondent could choose to fill the card out to enter a lottery to win Home Depot gift cards.[ii] Figure 1 shows a map of the western Lake Erie basin, including the Maumee River watershed, which is the largest in the Great Lakes Region and contributes, by far, the largest volume of sediment and nutrient loadings into Lake Erie (Reutter et al. 2011).

We received 766 total responses, out of which 753 provided useable information for our general summary, leading to a 25% response rate. Of these 753, 566 individuals indicated that they fished in Lake Erie in 2013, and over 80% of the respondents were from counties near the lake. The bulk of trips came from individuals living along or near the lake, and most trips occurred in summer and fall, with fewer trips in spring. Table 1 presents the comparison of demographic and socioeconomic characteristics of anglers in our sample with the sample of Ohio anglers in 2011 National Survey of Fishing, Hunting and Wildlife-Associated Recreation (U.S. Fishing and Wildlife Service and U.S. Census Bureau 2011). Compared to the sample in the national survey, our sample is skewed toward older anglers with higher household income and higher education, and consists of more anglers with a primary residence outside of a Metropolitan Statistical Area. In addition, on average the anglers in our sample have over 33 years of experience and a third of them already retired.

This article mainly relies on data from a section of the survey in which respondents were presented six hypothetical choice experiment scenarios to determine individual preferences for fishing in Lake Erie. Each scenario had two alternative, “hypothetical” walleye fishing sites in the lake. The sites vary in five characteristics, including the expected walleye catch rate (1, 2, 4, and 6 hours per fish per person),[iii] water quality indicated by the size of algal bloom through which the angler have to boat through to get to the fishing site (0, 4, or 8 miles), water clarity (very murky, somewhat murky, very clear), driving distance from angler’s house to their preferred boat ramps (15, 30, 45 minutes) and the boating time from the ramp to the fishing site (20, 40, 60 miles). In each scenario, the angler was asked to choose the walleye fishing trip that she would most prefer, with an option to choose neither of these two particular sites. We followed the D-efficient survey design principles (Ferrini and Scarpa 2007), and constructed 6 blocks, 72 sets of choice scenarios following the SAS Macros developed by Kuhfeld (2005). These choice scenarios were then randomly allocated to each angler. Figure 2 presents an example of the choice experiment scenario. We chose to represent the size of algal bloom as the distance of an algal bloom that the angler would need to boat through (from the shoreline) to get to the fishing site because, according to our pilot survey with 15 anglers, it was easier for anglers to understand and relate to their fishing experience compared to other measures like the probability of the algal blooms in Lake Erie.

In the choice experiment models, we calculated the travel cost of driving from home to the nearest boat ramp, assuming the gasoline costs for driving on land are $0.52 per mile. We also assume the opportunity cost of time is 30% of the wage rate (Cesario 1976), and the wage rates are calculated from the annual income by dividing by 2,000 hours worked per year.

Results

Table 2 presents the regression results of four different discrete choice models, including CL, RPL, S-MNL with price scaled by the scaling factor and G-MNL-II; while table 3 reports the results from a 4-class LCM. We also present additional robustness checks in the Appendix, including CL with interactions, S-MNL with price unscaled, as well as two alternative RPL models with lognormal distributions for certain water quality variables. The optimal number of classes in the LCM is selected based on the lowest Adjusted Bayesian Information Criterion (ABIC), and the results for the LCM class number selection are available from authors upon request. In addition to the estimated regression coefficients and standard deviations, we also report two measures in order to compare and evaluate the model performance. The log-likelihood measures the goodness-of-fit while the out-of-sample prediction accuracy measures the percentage of accurate prediction for the remaining 25% sample when the other 75% sample randomly selected are used in the estimation. Unsurprisingly, the log-likelihood increases when the preference heterogeneity across anglers is accounted for using individual-specific mean utility weights as in RPL. However, a greater gain in goodness-of-fit is achieved when the scale heterogeneity across individuals is also taken into account, yielding the G-

MNL-II, which in a way combines RPL and S-MNL, as the best model in terms of goodness-of-fit in table 2. The LCM performs even better than G-MNL-II in terms of goodness-of-fit. The story based on out-of-sample prediction accuracy is similar: the two models that have the highest out-of-sample prediction accuracy are G-MNL-II and LCM, suggesting that based on these two measures, G-MNL-II and LCM are the "best" performing models with our data.

There are several things worth noting regarding the signs and magnitudes of the estimated coefficients and standard deviations. First, the mean estimated coefficients for the travel cost and water quality attributes have the expected signs across all discrete choice models shown in table 2. On average, Ohio anglers dislike fishing sites that are too far away or more costly, and they prefer clearer water, higher walleye catch rates, and a smaller HAB size to boat through. Secondly, there is substantial heterogeneity across the estimated coefficients for all four water quality attributes, as shown by the significant coefficients for the standard deviation in RPL and G-MNL-II as well as the significant scale parameter in S-MNL and G-MNL-II. Finally, table 3 reveals that discrete classifications across Ohio recreational anglers using LCM could be informative: anglers in class 1 care less about water clarity, while class 3 anglers have a relatively lower valuation for the improvements in walleye catch rates; class 2 and class 4 anglers both have balanced valuation towards water quality attributes, however, class 2 anglers have much higher valuation for improvements in walleye catch rates while class 4 anglers value water clarity more.

To better interpret the regression coefficients, we translate the regression coefficients into the marginal willingness to pay (MWTP) shown in table 4 calculated using the ratio of estimated regression coefficient for one water quality attribute over the estimated coefficient for the travel cost. On average across the models, Ohio anglers are willing to pay \$36.77–\$53.96 for one less hour needed to catch one walleye, and \$9.02–\$9.63 for one less mile of an algal bloom to boat through. In addition to the mean MWTP, we also present the lower and higher bound of the 95^{th} confidence interval of the MWTP to illustrate the large heterogeneity in MWTP across individuals. Consider the estimates for HAB size reduction: according to the RPL model, Ohio anglers are willing to pay \$9.63 for a one-mile reduction in HAB size, but the distribution of this MWTP spans from \$7.30 to \$11.96. Similarly the range implied by the G-MNL-II model for HAB size reduction is \$7.34 to \$11.15.

While there is not a large range across the mean WTP for size of HABs through which one must boat, there is considerable heterogeneity within each model (Figure 3). This wide distribution in willingness to pay suggests that there is potentially substantial heterogeneity amongst anglers with respect to HAB values. The LCM distribution has multiple spikes, as expected, given the discrete nature of the mixing distribution, and it provides insight into which types of individuals are more heavily affected by HABs. Individuals in class 4 have the largest welfare losses, and tend to be older, likely retired, and male. Given this demographic, they potentially have more experience fishing, and thus the change in environment as a result of increasing HABs causes them more harm. The S-MNL has a positive skew, potentially accounting for the positive value most anglers will place on reducing HABs, and the longer tail accounts for the relatively smaller group of anglers who have extremely high values for HAB size reduction. This is consistent with the finding using LCM. Figure 3 also shows that due to the presence of these high-valuation anglers, approaches that do not account for heterogeneity tend to over-estimate the average willingness to pay.

To evaluate the implications of nutrient management policies on water quality outcomes and the value anglers place on improving water quality, we develop estimates of welfare benefits for three policy scenarios based on potential reductions in dissolved phosphorus loadings from the Maumee River watershed (table 5). The three scenarios consider 10%, 20%, and 40% reductions in dissolved reactive phosphorus loads. The large 40% reduction is based on the recommendation of Ohio's Lake Erie Phosphorus Task Force (Ohio Lake Erie Phosphorus Task Force 2013). For each policy scenario, we evaluate the impact on HAB size, water clarity, and walleye fishing population using a three-dimensional coupled Lake Erie hydrodynamic lower food-web model (Fraker et al. 2015). The following water quality attributes capture the current baseline condition of Lake Erie: it takes roughly 2.2 hours on average to catch one walleye and 6 miles of HAB to boat through to reach the desired fishing site, and the water in Lake Erie is somewhat murky. The hydrodynamic model and a statistical model that links Maumee nutrient loadings and walleye catch rates (Ludsin, DeVanna, and Smith 2014) suggest that there would be no improvement in the walleye catch rates in the western and central basins of Lake Erie with a reduction in nutrient runoff. In contrast, a reduction in phosphorus loadings would reduce HAB size and it would improve water clarity. The models suggest that improvements in water quality are nonlinear, with the 10% and 20% nutrient reductions having a small effect in comparison to the 40% reduction.

Table 6 shows the distribution of compensating variation (CV) across these three nutrient management policy scenarios and five discrete choice models following equations (9) and (10). Intuitively, anglers' willingness to pay for the nutrient management policies increase with the magnitude of nutrient reduction, and anglers expressed the greatest gains in CV for a change from 20% nutrient reduction to 40% nutrient reduction. Specifically, Ohio anglers are willing to pay an average of \$11–\$17 for a 20% reduction in DRP loadings from Maumee, and more than double that amount, \$29–\$48 on average for a 40% DRP loading reduction. This consistent with the nonlinearity of the production of ecosystem services that a larger reduction in nutrient runoff is needed to generate sizeable ecosystem services. There is significant heterogeneity in willingness to pay across individuals in the sample, as expected. It is also worth noting that models that explicitly incorporate heterogeneity in angler preferences in the most flexible fashion, LCM and G-MNL-II, yield a lower average welfare measure, at least for small changes in nutrients. In contrast, CL and RPL does not fully account for the subset of anglers who have extremely high valuation for water quality attributes. To accommodate the presence of these high-valuation subgroups, the CL and RPL normal mixing distribution seem to shift upwards to account for the extremely high coefficients for these anglers and thus often results in a higher mean MWTP.

Conclusion

The Great Lakes ecosystem is heavily affected by elevated P loadings from agriculture that have degraded water quality and increased the incidence and intensity of HABs. In particular, many of the valuable ecosystem services provided by Lake Erie are significantly affected, including its $1.5 billion sport fishing industry. Using a mail survey of 767 Ohio recreational angler respondents and a discrete choice experiment, we provide the first empirical evidence in the US to link HABs to damages to Great Lakes recreational anglers. Specifically, we use a discrete choice experiment with varying water quality characteristics at two Lake Erie fishing sites, including walleye catch rates, miles of HABs to boat through en route to the fishing site, water clarity, and boating distance and travel cost from home to nearest boat ramp. In addition to the standard CL model, which has restrictive substitution patterns due to the IIA assumption, we estimate four other discrete choice models to uncover the heterogeneous preferences among Ohio recreational anglers for water quality improvements: RPL and LCM account for unobserved taste heterogeneity by allowing for the continuous or discrete random coefficients for observed characteristics, while S-MNL and G-MNL-II accounts for the randomness of the decision-making using a scale heterogeneity parameter.

We find significant economic benefits for Ohio recreational anglers associated with water quality improvements in Lake Erie, and this substantial valuation varies greatly among individual anglers, suggesting that it is critical to account for heterogeneous preferences among Ohio anglers. Specifically, Ohio anglers are on average willing to pay as much as $9–$10 for one less mile of HAB to boat through before reaching the desired fishing site. We estimated the compensating variation for four different nutrient management policies that would reduce the agricultural phosphorus loadings from Maumee River watershed, the biggest tributary in the western Lake Erie basin and the largest source of nutrient impairment. On average, Ohio recreational anglers are willing to pay as much as \$29–\$48 for a policy that would cut the dissolved reactive phosphorus loadings from Maumee by 40%, which would lead to a \$2.9–\$4.8 million welfare loss, assuming 10% of trips are affected for the over 1 million Ohio recreational anglers.

This article provides the first empirical evidence that links HABs and excessive agricultural pollution in the Lake Erie watershed to significant losses in ecosystem services as shown by economic damages to a multi-billion recreational fishing industry. We also demonstrate the importance of accounting for individual anglers' heterogeneous preferences for water quality improvements, which is especially important when recent occurrences of HABs at varying spatial and temporal scale pose significant uncertainty in the fishing experience. By focusing on a random sample of Ohio recreational anglers, we underestimate the economic damages to the entire Lake Erie recreational fishery due to the omission of anglers from Michigan, New York, Indiana, and Canada.

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Tables

Table 1. Comparison of Angler Characteristics of our Sample and National Sample

Variable	Value	Our sample # responses	Our sample percentage	National sample percentage
Age	18-24 years	12	1.6%	16.1%
	25-34 years	54	7.0%	17.6%
	35-44 years	75	9.8%	13.3%
	45-54 years	165	21.5%	31.1%
	55-64 years	196	25.6%	7.1%
	65-74 years	265	34.6%	14.7%
Education	11 years or less	26	3.5%	11.5%
	12 years	168	22.4%	51.8%
	1 -3 years of college	278	37.0%	16.6%
	4 years or more of college	279	37.2%	20.1%
Annual household income	less than 20k	59	8.8%	28.0%
	20-30k	46	6.9%	11.8%
	30-40k	85	12.7%	14.2%
	40-50k	30	4.5%	6.0%
	50-75k	163	24.3%	18.1%
	75-100k	116	17.3%	8.0%
	100-150k	171	25.5%	13.9%
Population size of residence	1 million or more	285	37.2%	30.2%
	250k - 1 million	75	9.8%	32.5%
	50k to 250k			25.5%
	Outside MSA	407	53.1%	11.8%
Sex	Male	672	89.0%	80.1%
	Female	83	11.0%	19.9%

Table 2. Model Results from CL, RPL, S-MNL and G-MNL-II Models

Variable	Explanation	CL	RPL	S-MNL	G-MNL-II
Mean coefficient					
price	travel cost from home to nearest boat ramp ($)	-0.0069*** (0.0008)	-0.0126*** (0.0012)	-0.0163*** (0.0015)	-0.0208*** (0.0018)
walleye	# hours to catch one walleye	-0.3205*** (0.0125)	-0.6805*** (0.0345)	-0.7353*** (0.0451)	-1.0170*** (0.0682)
hab_size	miles of algal bloom to boat through	-0.0627*** (0.0065)	-0.1214*** (0.0120)	-0.1548*** (0.0131)	-0.1878*** (0.0172)
clarity_clear	dummy for very clear water	0.6557*** (0.0521)	0.9440*** (0.0888)	1.1045*** (0.1107)	1.3571*** (0.1499)
clarity_medium	dummy for somewhat murky water	0.4433*** (0.0521)	0.5998*** (0.0767)	0.6105*** (0.0959)	0.8604*** (0.1243)
dist_boat	boating distance from boat ramp to fishing site (miles)	-0.0068*** (0.0017)	-0.0214*** (0.0035)	-0.0230*** (0.0027)	-0.0271*** (0.0036)
neither	dummy for choosing "neither"	-1.7484*** (0.0953)	-3.9268*** (0.1735)	-3.8531*** (0.1302)	-4.5751*** (0.1845)
Standard deviation					
walleye	# hours to catch one walleye		0.5633*** (0.0345)		0.6688*** (0.0578)
hab_size	miles of algal bloom to boat through		0.1734*** (0.0157)		0.1670*** (0.0252)
clarity_clear	dummy for very clear water		1.1728*** (0.1197)		1.5028*** (0.1842)
clarity_medium	dummy for somewhat murky water		-0.5414*** (0.1745)		-0.0861*** (0.1666)

Table 2. continued

dist_boat	boating distance from boat ramp to fishing site (miles)			-0.0615*** (0.0038)		0.0252*** (0.0055)
tau	scale parameter				1.1225*** (0.0527)	1.0178*** (0.0560)
Log-likelihood			-4502.14	-3784.39	-3718.93	-3627.81
Out-of-sample prediction accuracy			50.7%	54.0%	53.5%	55.6%
Number of observations		13806				
Number of respondents		767				

Table 3. Latent Class Models with Four Classes

Variable	Explanation	Class 1	Class 2	Class 3	Class 4
Utility function					
price	travel cost from home to boat ramp ($)	-0.0208* (0.0109)	-0.0160*** (0.0025)	-0.0059*** (0.0015)	-0.0144*** (0.0026)
walleye	# hours to catch one walleye	-0.7091** (0.3173)	-1.1674*** (0.1003)	-0.036*** (0.0281)	-0.4753*** (0.0502)
hab_size	miles of algal bloom to boat through	-0.2272** (0.0939)	-0.1542*** (0.0272)	-0.0455*** (0.0115)	-0.1588*** (0.0215)
clarity_clear	dummy for very clear water	0.5911 (0.5472)	0.7567*** (0.1706)	0.5089*** (0.0973)	1.7339*** (0.1987)
clarity_medium	dummy for somewhat murky water	-0.2498 (0.6211)	0.6027*** (0.1661)	0.4299*** (0.0892)	1.0100*** (0.1820)
dist_boat	boating distance from boat ramp to fishing site (miles)	0.0161 (0.0231)	-0.0297*** (0.0031)	-0.0007 (0.0031)	-0.0145*** (0.0054)
neither	dummy for choosing "neither"	-0.8202 (1.2650)	-7.7773*** (0.6022)	-3.0586*** (0.2917)	-1.6675*** (0.3489)
Class membership function					
age	age of respondent	-0.0292** (0.0131)	-0.0294** (0.0131)	-0.0117 (0.0137)	
education	highest level of education	-0.2134 (0.1489)	0.2161* (0.1259)	-0.1674 (0.1265)	
employed	working or self-employed	-1.4289** (0.6309)	-0.9181 (0.6082)	-0.9207 (0.6163)	
male	dummy for male	-0.1516 (0.4502)	-0.2448 (0.3900)	-0.0792 (0.3993)	

Table 3. continued

household income	household income		-1.02E-06 (4.28E-06)	5.41E-06 (3.32E-06)	-7.82E-07 (3.34E-06)	
married	dummy for married		0.2047 (0.3453)	0.3439 (0.2960)	0.5054* (0.2929)	
retired	dummy for retired		-0.6340 (0.6614)	-0.8665 (0.6490)	-0.4748 (0.6416)	
constant	intercept		2.8177*** (1.0110)	1.6090 (0.9970)	1.7539* (1.0362)	
Latent class share			0.136	0.306	0.322	0.235
Log-likelihood		-3328.36				
Out-of-sample prediction accuracy (%)		54.8%				
Number of observations		13806				
Number of respondents		767				

Table 4. Heterogeneity in WTP across Various Models

Marginal changes	MWTP	CL	RPL	S-MNL	G-MNL-II	Mean	Latent class model			
							Class 1	Class 2	Class 3	Class 4
One more hour to catch one walleye	mean	-46.79	-53.96	-45.05	-48.84	-36.77	-34.16	-73.04	-6.10	-33.04
	low	-60.67	-64.56	-53.36	-58.15	-73.04				
	high	-37.96	-43.36	-36.73	-41.62	-6.10				
one more mile of an algal bloom to boat through	mean	-9.16	-9.63	-9.48	-9.02	-9.53	-10.95	-9.64	-7.71	-11.04
	low	-11.94	-11.96	-11.52	-11.15	-11.04				
	high	-6.99	-7.30	-7.44	-7.34	-7.71				
Water clarity changes into very clear	mean	95.72	74.85	67.67	65.17	74.51	28.47[a]	47.35	86.25	120.53
	low	74.53	56.53	53.55	51.87	28.29				
	high	125.31	93.17	81.78	81.01	120.48				
Water clarity changes into somewhat murky	mean	64.72	47.56	37.40	41.32	53.16	12.03[a]	37.71	72.85	70.21
	low	47.02	33.28	25.97	30.76	12.03				
	high	88.29	61.84	48.83	54.99	72.85				
One more mile from boat ramp to fishing site	mean	-0.99	-1.70	-1.41	-1.30	-0.74	0.77[a]	-1.86	-0.12[a]	-1.01
	low	-1.55	-2.31	-1.82	-1.76	-1.86				
	high	-0.45	-1.09	-1.00	-0.93	0.77				

Note: MWTP is marginal willingness to pay. Low and high are the lower and higher bound of the 95th confidence interval.
[a]denotes the WTP that is not statistically significant.

Table 5. Impacts of Different Nutrient Management Policies on Water Quality Variables

Policy scenario		Variable values			
Number	**Description**	***walleye***	***hab_size***	***clarity_clear***	***clarity_medium***
	baseline	2.2	3	0	1
1	10% reduction in Maumee DRP loading	2.2	3	0.2	0.8
2	20% reduction in Maumee DRP loading	2.2	2.5	0.3	0.7
3	40% reduction in Maumee DRP loading	2.2	1	0.7	0.3

Note: DRP denotes dissolved reactive phosphorus.

Table 6. Distribution of Welfare Effects across Nutrient Management Scenarios and Models

Policy % reduction	CV	CL	RPL	RPL-LogNormal	S-MNL price scaled	S-MNL price unscaled	G-MNL-II	LCM
10	mean	6.20	5.63	8.27	6.05	8.28	4.61	4.91
	std dev		11.50	16.17		6.96	9.20	3.14
	median		5.20	5.04		5.66	4.11	2.80
	low		-24.58	-26.33		1.64	-16.46	1.94
	high		30.83	53.19		34.52	27.04	10.06
20	mean	13.88	13.31	12.41	13.82	17.45	11.14	12.15
	std dev		17.64	24.25		12.59	13.89	5.22
	median		13.13	7.56		12.88	10.47	8.35
	low		-34.03	-39.49		3.83	-20.89	7.72
	high		54.99	79.80		56.42	46.51	20.60
40	mean	40.02	39.17	28.96	40.27	48.38	33.04	38.76
	std dev		43.14	56.58		32.91	32.99	14.60
	median		38.45	17.64		36.58	31.97	28.07
	low		-76.36	-92.15		11.19	-45.35	26.13
	high		138.27	186.19		142.54	119.14	62.30

Note: std dev denotes standard deviation of the compensating variation distribution, while low and high are the lower and higher bound of 99th confidence interval of compensating variation.

Figures

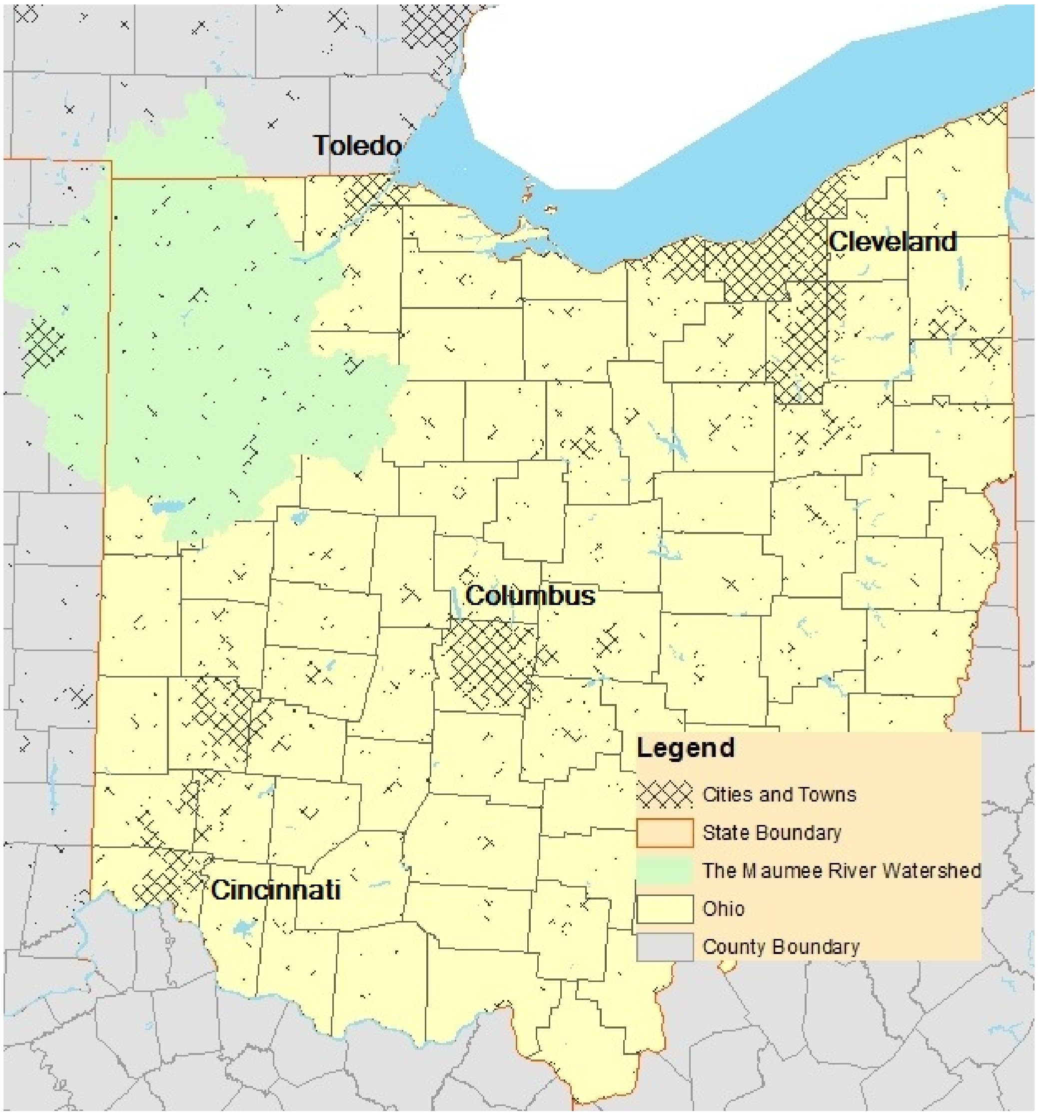

Figure 1. Study area – western Lake Erie basin.

Scenario 1 (9):

In the following scenario, two potential sites for walleye fishing are presented. Please review the attribute levels for each site, and decide which site you would prefer. Check the box below the particular site for the one you would choose. You can choose neither by checking the box "Neither".

Attribute	**Site A**	**Site B**	**Neither**
Walleye catch rate at fishing site (# hours needed per fish caught per person)	6 hours	2 hours	
Miles of an algal bloom that you have to boat through before getting to the fishing site (0, 4, 8)	8	0	
Poor water clarity caused by sediments at fishing site (Very murky, somewhat murky, clear)	Very Clear	Very Murky	
Time in boat getting to fishing site (minutes)	30	45	
Distance from house to boat ramp (miles)	40	20	
Which Site do you MOST prefer (Please check the box for your preferred option)	**Site A** ☐	**Site B** ☐	**NEITHER** ☐

Figure 2. One example of choice scenario in the choice experiment.

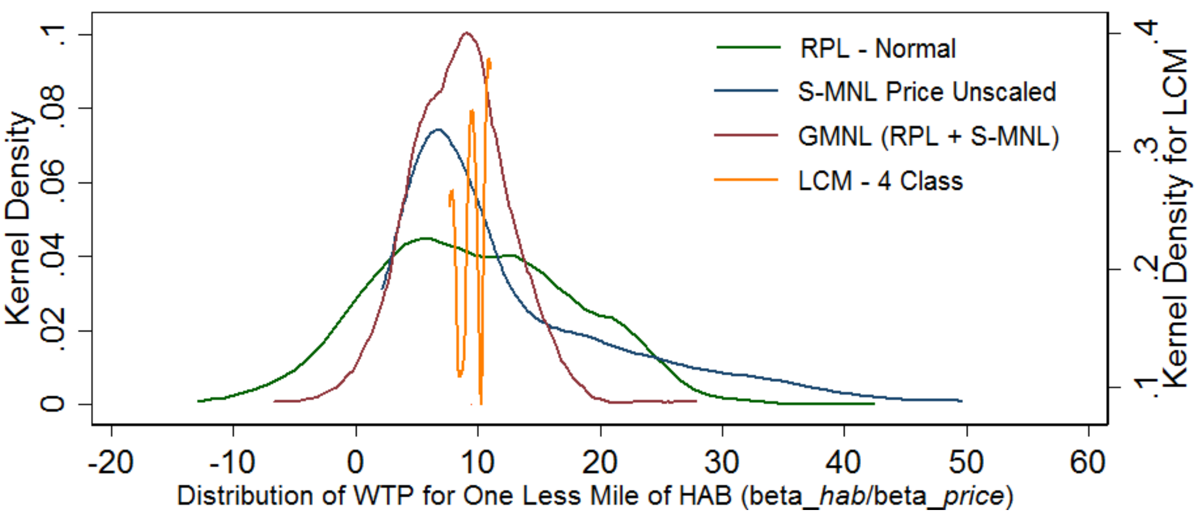

Figure 3. Distribution of WTP for one less mile of HAB.

Appendix

Variable	Explanation	CL w Interactions	S-MNL price unscaled	RPL – R1	RPL – R2
Mean coefficient					
price	travel cost from home to nearest boat ramp ($)	-0.0081*** (0.0009)	-0.0084*** (0.0009)	-0.0105*** (0.0011)	-5.2931*** (0.2641)
walleye	# hours to catch one walleye	-0.3311*** (0.0196)	-0.8929*** (0.0636)	-0.6775*** (0.0774)	-0.7967*** (0.0615)
hab_size	miles of algal bloom to boat through	-0.0859*** (0.0281)	-0.1852*** (0.0163)	-0.0954*** (0.0103)	-3.2359*** (0.2527)
clarity_clear	dummy for very clear water	0.6346*** (0.0600)	1.0513*** (0.1221)	0.8673*** (0.0774)	0.8504*** (0.0754)
clarity_medium	dummy for somewhat murky water	0.4293*** (0.0597)	0.4939*** (0.1000)	0.5319*** (0.0677)	0.5524*** (0.0695)
dist_boat	boating distance from boat ramp to fishing site (miles)	-0.0056*** (0.0020)	-0.0286*** (0.0031)	-0.0112*** (0.0026)	-0.0116*** (0.0025)
neither	dummy for choosing "neither"	-1.2164*** (0.1537)	-3.8061*** (0.1251)	-3.7673*** (0.1570)	-3.9802*** (0.1648)
Interaction Variables					
*walleye*walleye is the key species to target*	# hours to catch one walleye * dummy_key species to target is walleye	0.0167 (0.0206)			
*hab_size*has seen HAB*	miles of algal bloom to boat through * dummy_has seen blooms before	0.0208 (0.0284)			
*neither*male*	dummy_choose “neither” * dummy_male	0.0661*** (0.0192)			

Appendix continued

*neither*education*	dummy_choose "neither" * education level	-0.2082***			
		(0.0376)			
Standard deviation					
price	travel cost from home to nearest boat ramp ($)				-2.5044***
					(0.2316)
walleye	# hours to catch one walleye			1.4161***	0.9362***
				(0.0714)	(0.0503)
hab_size	miles of algal bloom to boat through			-0.3584*	0.0247***
				(0.1905)	(0.0034)
clarity_clear	dummy for very clear water			0.8355***	-0.7321***
				(0.1178)	(0.1177)
clarity_medium	dummy for somewhat murky water			-0.3584*	0.4520***
				(0.1905)	(0.1387)
dist_boat	boating distance from boat ramp to fishing site (miles)			-0.0337*	0.0247*
				(0.0034)	(0.0034)
tau	scale parameter		1.3401***	-0.0337*	0.0247*
			(0.0634)	(0.0034)	(0.0034)
Log-likelihood		-3429.36	-3746.26	-3720.46	-3655.14
Out-of-sample prediction accuracy (%)		53.5%	52.7%	52.4%	53.1%
Number of observations				13806	
Number of respondents				767	

Note: RPL-R1 treats the distribution of the coefficient for *walleye* as lognormal, and RPL-R2 treats the distribution of the coefficients for *walleye*, *price* and *hab* as lognormal

Grouped Footnotes

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[i] The counties alongside the shoreline of Lake Erie are Lucas, Ottawa, Sandusky, Erie, Lorain, and Cuyahoga; while the counties close to but not along the shoreline included in the survey are Wood, Seneca, Huron, and Medina.

[ii] For the second 1,000 anglers, three gift cards with $200, $150, or $100 are available for the lottery winners while the last 1,000 anglers could enter the lottery to win one of the six gift cards with $75 for each.

[iii] The typical walleye catch rate in Lake Erie is estimated by Ohio Department of Natural Resources to be about 2.2 hours of fishing for one fish per person for the typical angler.