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The Economic Impacts of Harmful Algal Blooms and E. Coli on Recreational Behavior in Lake Erie

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#### Abstract

Lake Erie has been plagued by the emergence and growth of harmful algal blooms (HABs) for nearly 20 years. This paper quantifies HAB-related impacts on Lake Erie recreators using survey data collected from Ohio recreators who visited Lake Erie during the summer of 2016. We combine survey responses on visitation with information on harmful algal blooms acquired from remote-sensing data. Using simulation based on latent class models of recreation choice, we find that beach-goers and recreational fishermen would lose in aggregate $\$ 5.3$ million and $\$ 59.2$ million respectively each year if water conditions became so poor that Lake Erie's western basin was closed. In counterfactual simulations, we find significant welfare gains associated with a $40 \%$ reduction in phosphorus loadings, which is an objective set by the 2012 Great Lakes Water Quality Agreement (GLWQA). Finally, we recover heterogeneity in recreators' aversion towards algae and Escherichia coli (E. coli), with beach-goers more averse to E. coli and fishermen more averse to algae, indicating that water quality remediation policies will have strong distributional effects.


Keywords: harmful algal blooms; recreation demand; Lake Erie; E. coli, welfare

JEL Codes: Q51, Q53, Q57, C83

## The Economic Impacts of Harmful Algal Blooms and E. Coli on Recreational Behavior in Lake Erie

Harmful algal blooms create freshwater toxins that are dangerous to humans and animals, raising public concern due to increasing occurrences both in the U.S. and globally (Morse et al. 2011; Duan et al. 2009; Bowling and Baker 1996). Apart from the direct adverse impacts on human health via drinking water provision, HABs also have the potential to significantly reduce welfare through negative impacts on economic activities. For example, degradation in lake water quality has been shown to reduce the value of nearby properties (Wolf and Klaiber 2017; Walsh et al. 2011; Leggett and Bockstael 2000) and the demand for recreational amenities (Wolf et al. 2017; Keeler et al. 2015; Hanley et al. 2003; Bockstael et al. 1987).

A substantial body of literature on the impact of environmental change on recreational demand uses discrete choice modeling methods, combined with either survey responses of recreation behavior or site intercept data, to reveal the latent preferences of recreators. In this paper, we conduct a web-based survey of randomly selected households across 18 Ohio counties near the Lake Erie shoreline and collect information on trips to Lake Erie during the summer of 2016. The western basin of Lake Erie suffers from repeated exposure to harmful algae during the summer months, including recent contamination of local drinking water sources for the city of Toledo, Ohio, which affected over 500,000 residents. We obtained responses from 749 individuals with 549 of those individuals taking at least one day trip to one of 106 access locations along the Lake Erie shoreline.

Previous studies that value water quality changes using travel cost models mainly focused on how pathogens, such as E. coli (Murray et al. 2001), or beach closures (Palm-Forster et al. 2016; Parsons et al. 2009) influence recreation behavior. Harmful algal blooms have received less attention in the literature,
likely due to the difficulty in observing varying concentrations of HABs. One notable exception is the recent analysis by Zhang and Sohngen (2018) which finds anglers are willing to pay $\$ 8$ to $\$ 10$ more per trip for every one less mile of boating through HABs. In this paper, we create a novel dataset to simultaneously examine the effects of $E$. coli and HABs by combining responses on recreation behavior with detailed geospatial data on harmful algal blooms gathered from the National Oceanic Atmospheric Administration (NOAA), and site-specific characteristics provided by the Ohio Department of Natural Resources (ODNR).

Using this dataset, we estimate the welfare costs of blue-green algal blooms on recreational beach users along the Lake Erie shoreline in Ohio. We make three contributions to the literature - (1) we use information on recreational behavior to provide new valuation estimates of the negative impact of harmful algal blooms, (2) we show that heterogeneity in individual preferences for lake shore amenities and disamenities-willingness to pay to avoid harmful algal blooms and E. coli-will likely lead to strong distributional effects from remediation policies, and (3) we predict the value of welfare losses from algal blooms and benefits from algae control under four hypothetical policy scenarios.

## II. Survey Design and Data

The sample frame consists of 20,000 residential mailing addresses for single-family homes located within 50 miles from the Lake Erie shoreline, randomly drawn from 18 counties across the state of Ohio (Figure [1]). Addresses were collected from county tax auditors databases. For each address selected, two postcards were sent out: one in the first week of February 2017 and a second in the last week of February of 2017. Each postcard included a brief description of the study along with a URL website address, directing the recipients to an online survey. A unique identification number was also included
on each postcard and was subsequently entered into the online survey by respondents, allowing us to link survey responses with residential location information from the auditor data.

The online questionnaire contained three sections. The first section asked recipients questions about their typical day trip to Lake Erie between Memorial Day (05/30/2016) and Labor Day (09/05/2016), total trips taken to Lake Erie in the summer of 2016, travel mode to Lake Erie, ranking of site characteristics that were considered most important when deciding where to go, and if the respondent was aware of algae in Lake Erie or of any water quality advisories. In the second section respondents were guided through an interactive map of 185 access points monitored and managed by the Ohio Department of Natural Resources (ODNR), Office of Coastal Management to determine time and location of the most recent day trip to Lake Erie. Survey respondents then reported expenditures on gas, food, clothing, parking, etc., the primary purpose of their trip (i.e. boating, fishing, swimming, etc.) and perceived congestion at the chosen site. The final section contained questions on demographic characteristics (income, race, education, etc.). After removing non-recreational trips and respondents who took more than 3 hours to finish the survey, the final sample contains 749 responses. Of these, 549 took at least one-day trip to one of 106 different locations along the Lake Erie shoreline.

To understand and model motivations for recreation trips, we asked individuals to rate the importance of 11 site characteristics using a five-point Likert Scale (Figure [2]). Survey-respondents indicate more concern for the quality/availability of natural amenities than man-made amenities. The overall beauty, health, clarity and odor of the water are important, with $90 \%$ of respondents indicating these attributes are either very important or extremely important in deciding where they choose to recreate along Lake Erie. Available parking, boating opportunities and convenient facilities are less
important. Given the importance placed on water quality, it is reasonable to expect that differences in algal concentrations across sites likely influence recreational location decisions.

Table [1] shows the demographics of our survey-respondents compared to those of the general population living within the 18 counties either bordering or located near Lake Erie. We note a number of differences between our sample of recreational visitors and the general population. The surveyed sample tends to be more educated, wealthier, have a larger household, and live in more rural areas than the general population. Although our sample is not representative of the entire population, it is more representative of the general population than similar samples (Table [1]) collected by the Ohio Department of Natural Resources $(N=1,513)$ and the U.S. Fish and Wildlife Service $(N=1,435)$ between 2007 and 2011. The average Ohio Department of Natural Resources respondent is more likely to be male, have higher educational attainment status and more likely employed than the general population of Ohio. Likewise, the U.S. Fish and Wildlife Service sample is disproportionately white, male, poor, rural, and has a lower level of education than the overall population.

We obtained water quality data from NOAA and Stumpf et al. (2012), and merged this information with site-specific characteristic information provided by the Ohio Department of Natural Resources. NOAA publishes 10-day harmful algal bloom composites for Lake Erie, measured in microcystis cells $(10,000 s$ per mL$)$, between the months of June and October. Given the lack of blooms during June of 2016 however, NOAA only published composites between July $1^{\text {st }}$ and October $30^{\text {th }}$ for 2016 . Using this dataset, we create a site-specific, summer-long mean algae measure using only readings collected from the closest remote sensing location. Similarly, maximum Ohio Department of Health E. coli readings from the closest monitoring station were also attached to each access point. Finally, we include proximity to
other non-Lake Erie amenities as measured by the distance between each access point and Cleveland and Toledo's central business district.

Table [2] reports summary statistics for site-specific characteristics. On average, Lake Erie access points had a beach, accessible parking nearby, restrooms, a picnic area and walkable trails. Sites with algae conditions above 100,000 cells/mL are above the World Health Organization's high advisory threshold, while the Environmental Protection Agency issues E. coli health advisories when conditions surpass $410 \mathrm{CFU} / \mathrm{mL}$ (EPA 2012). As needed for modeling site choice, algae and E. coli levels vary substantially across sites during 2016.

## III. Demand for Recreation

Following a standard discrete-choice random utility maximization framework (Haab and McConnell 2002;

McFadden 1974), on each choice occasion, each recreator faces a site choice of where to access Lake Erie from among 106 possible locations. The utility of a trip to a chosen site is a function of the cost of traveling to the site, and other site-specific attributes including environmental quality.

Following Dundas et al. (2018), we use income data, and a spatial matrix of distances between each site and mailing address to calculate the travel cost to each site for each respondent:

$$
\text { Travel Cost }{ }_{i j}=2 *\left[\left(\text { wages }_{i} / 3\right) *\left(\text { dist }_{i j} / 55 \mathrm{mph}\right)+\left(\text { dist }_{i j} * 0.476\right)\right]
$$

where Travel Cost ${ }_{i j}$ measures the cost of traveling to site $j$ for individual $i$. The first component of Travel Cost $_{i j}$ represents the opportunity cost of travel time and is defined as the distance traveled at $55 \mathrm{mph}\left(\right.$ dist $\left._{i j} / 55 \mathrm{mph}\right)$ multiplied by one-third of the wage rate (wages ${ }_{i} / 3$ ) (Haab and McConnell 2002), where wages $s_{i}$ represents individual i's hourly wage rate calculated by dividing annual income
by 2000 hours $^{1}$ and dist $_{i j}$ is the one-way distance in miles from respondent $i$ 's residence to access point $j$. The second component of Travel $\operatorname{Cost}_{i j}$ is an approximation of the out-of-pocket cost of driving (dist ${ }_{i j}$ * 0.476). According to the American Automobile Association (2016), the average per mile cost of operating a vehicle in 2016 was $\$ 0.476$. This includes the cost of gas, maintenance and vehicle depreciation. One-way travel costs are doubled to give a measure of round-trip travel costs.

Finally, respondents were given a choice between seven different activities at the chosen recreation site, some of which included direct interaction with the water (i.e. boating, swimming, fishing, etc.), while other activities were less water-focused (i.e. wildlife watching, walking/running, etc.). Participants were also given the chance to write in their own activity if none of seven provided categories accurately described their recreational activity. Summary statistics for the travel cost estimate and the visitor's primary purpose of recreating are given in Table [3].

Assuming recreators are utility maximizers, the individual will choose the site that maximizes the utility of taking a trip on that choice occasion. Each household, $i$, is assumed to maximize utility given by

$$
\text { (1) } U_{i j}=V_{i j}+\varepsilon_{i j}
$$

where $V_{i j}$ is an observed component of utility for household $i$ choosing to recreate at site $j$, and $\epsilon_{i j}$ is an idiosyncratic component of utility unobserved to the researcher. The representative utility, $V_{i j}$, captures the effects of observed attributes that vary among individuals, sites or both. The idiosyncratic error term is assumed to be distributed i.i.d. type I extreme value giving rise to the well-known logit family of models with probability of individual $i$ choosing site $l$ given by:

[^0]$$
\text { (2) } P_{i l}=\frac{\exp \left(V_{i l}\right)}{\sum_{j=1}^{J} \exp \left(V_{i j}\right)}
$$

Modeling variation and preference heterogeneity is introduced through treatment of covariates in the specification of the indirect utility function and its parameterization. Consider the standard specification of representative utility:

$$
\text { (3) } V_{i j}=\gamma Z_{i j}+X_{j}^{\prime} \boldsymbol{\beta}
$$

where $Z_{i j}$ denotes the individual and site-varying travel cost for person $i$ visiting site $j, X_{j}$ is a vector of site specific attributes including water quality measures, $\gamma$ is a scalar representing the marginal utility of income (to be estimated) and $\boldsymbol{\beta}$ is a vector of taste parameters to be estimated.

Without individual preference heterogeneity, the parameters in equation (3) can be estimated using a standard fixed parameter logit maximum likelihood estimation routine. To introduce preference heterogeneity, we assume the population is categorized into $S$ unobservable (latent) classes ( $s=$ $1, \ldots, S)$. For each group a unique set of parameters is estimated which allows consumers' tastes for site-varying attributes to vary across segments of the population. ${ }^{2}$ With preference heterogeneity, equation (2) becomes:

$$
\text { (4) } P_{i l \mid s}=\frac{\exp \left(\gamma Z_{i l}+X_{l}^{\prime} \boldsymbol{\beta}_{s}\right)}{\sum_{j=1}^{J} \exp \left(\gamma Z_{i j}+X_{j}^{\prime} \boldsymbol{\beta}_{s}\right)}
$$

where the probability of individual $i$ visiting site $l$, conditional on being in segment $s$, is equal to $P_{i l \mid s}$. As a part of the latent class model, a membership function must also be specified which assigns each individual into a specific segment of the population. Following Swait (1994) and Boxall and Adamowicz (2002), we specify this membership function using the following set of equations:

[^1](5) $M_{i s}=\psi_{s}+\psi_{s} D_{i}+\psi_{s} V_{i}^{*}+\xi_{i s}$
(6) $V_{i}^{*}=\theta_{V} Z_{i}+\mu_{i V}$
where $M_{i s}$ is the membership likelihood function for individual $i$ and segment $s ; D_{i}$ is a vector of observed sociodemographic characteristics of recreator $i ; V_{i}^{*}$ is a vector of latent psychometric constructs held by recreator $i ; Z_{i}$ is a vector of observed indicators of latent constructs held by respondent $i ; \psi$ and $\theta$ are parameter vectors to be estimated, and $\mu$ and $\xi$ represent error terms. Assuming $\xi$ is an i.i.d. error term with a Type I extreme value distribution, the probability of membership into group $s$ for individual $i$ can then be characterized by the following:
$$
\text { (7) } P_{i s}=\frac{\exp \left(\psi_{s}+\psi_{s} D_{i}+\psi_{s} V_{i}^{*}\right)}{\sum_{s=1}^{S} \exp \left(\psi_{s}+\psi_{s} D_{i}+\psi_{s} V_{i}^{*}\right)}
$$

The product of equations (4) and (7) then reveals individual $i$ 's unconditional probability of visiting site $l$ within a latent class framework:

$$
\text { (8) } P_{i l}=\sum_{s=1}^{S} P_{i l \mid s} * P_{i s}=\sum_{s=1}^{S} \frac{\exp \left(\gamma z_{i l}+X_{l}^{\prime} \boldsymbol{\beta}_{s}\right)}{\sum_{j=1}^{J} \exp \left(\gamma Z_{i j}+X_{j}^{\prime} \beta_{s}\right)} \frac{\exp \left(\psi_{s}+\psi_{s} D_{i}+\psi_{s} v_{i}^{*}\right)}{\sum_{s=1}^{S} \exp \left(\psi_{s}+\psi_{s} D_{i}+\psi_{s} V_{i}^{*}\right)}
$$

In the random parameters specification, on the other hand, there is even greater flexibility in preference heterogeneity as compared to the latent class model. Specifically, preference parameters are allowed to vary across individuals rather than segments. This additional flexibility can be observed in equation (9):

$$
\text { (9) } V_{i j}=\gamma Z_{i j}+\mathbf{X}_{j}^{\prime} \boldsymbol{\beta}_{i}, \quad \boldsymbol{\beta}_{\boldsymbol{i}} \sim \boldsymbol{N}\left(\boldsymbol{\mu}, \boldsymbol{\sigma}^{2}\right)
$$

where $\boldsymbol{\beta}$ now varies across individuals (i) rather than just segments $(s)$. One restriction with this approach, however, is the need to specify how the random parameters are distributed. Within our study we assume the coefficients on site-varying attributes to be normally distributed to aide in the interpretation of preference heterogeneity. Estimation of the mixed logit model proceeds by simulating
the choice probabilities given as

$$
\text { (10) } P_{i l}=\int \frac{\exp \left(\gamma Z_{i l}+X_{l}^{\prime} \boldsymbol{\beta}\right)}{\sum_{j} \exp \left(\gamma Z_{i j}+X_{j}^{\prime} \boldsymbol{\beta}\right)} f(\boldsymbol{\beta} \mid \boldsymbol{\mu}, \boldsymbol{\sigma}) d \boldsymbol{\beta}
$$

where $f(\boldsymbol{\beta} \mid \boldsymbol{\mu}, \boldsymbol{\sigma})$ is the probability density function of $\boldsymbol{\beta}$. Using simulated maximum likelihood we recover estimates of the parameters $\gamma, \boldsymbol{\mu}$, and $\boldsymbol{\sigma}$. With estimates in hand, we can use the familiar log-sum rule to estimate willingness to pay for non-marginal changes in covariates and the associated changes in utility (Small and Rosen 1981).

The three model specifications discussed above differ in the analysis of preference heterogeneity. The first specification of a conditional logit model in equation (3) holds consumer preferences for site attributes constant whereas both the latent class specification and mixed logit allow consumer preferences to be heterogeneous. It is important to allow for this additional heterogeneity in our study because there are different reasons why one might want to visit Lake Erie (i.e. boating, fishing, swimming, etc.), and depending on the purpose of the trip, the value of each observable site-attribute is expected to differ across individuals or groups. However, more generalizable models require additional assumptions. In the case of the mixed logit the distribution of the taste parameters must be specified in order to derive choice probability estimates. Latent class models are also more restrictive than conditional logit models as they require the specification of a membership function. However, the membership function allows latent class models to not only account for heterogeneity in consumer tastes, but also provides an explanation for the heterogeneity (Boxall and Adamowicz 2002).

## IV. Results

Table [4] reports estimates from both the conditional logit and mixed logit models of recreation choice.

Examining results from the conditional logit model first, we find the travel cost estimate to be, as
expected, negative and significant with a value of -0.049 . Site specific attributes also have the expected signs with positive and significant coefficients associated with picnic shelters, food services, showers, restrooms, and beach access. The coefficient on presence of boat ramps is negative, indicating potential congestion externalities associated with nearby boating to other recreators. Controlling for population centers, we find that households prefer recreation sites that are farther away from the densely developed Cleveland downtown whereas proximity to the less developed waterfront along Toledo was viewed positively.

Turning attention to the key water quality measures of interest-algae and $E$. coli-we find the expected negative and significant coefficients. The negative and statistically significant coefficient ( -0.007 ) on algae confirms our hypothesis HABs influence visitor decisions when they select recreation sites along Lake Erie. Similarly, the concentration of waterborne E.coli has a negative and significant (-0.1) impact on the decision-maker's site choice, consistent with the previous literature (Awondo et al. 2011; Murray et al. 2001).

We examine heterogeneity in preferences for site-attributes in a mixed logit model in Table [4] (column 2). Consistent with the discrete choice literature, we estimate a fixed preference parameter associated with travel cost to enable welfare calculations. Across all covariates we find that results are similar to the conditional logit model, with two notable exceptions. First, the mean coefficient on restrooms is insignificant. However, its standard deviation parameter is statistically significant. This suggests that while, on average, visitors are indifferent to the presence of restrooms there is significant heterogeneity across visitors. This is consistent with prior literature showing that particular segments of the population, generally families with kids, prefer recreation sites with restrooms (Parsons et al. 2009;

Timmins and Murdock 2007). Second, algae continue to have a negative and significant coefficient for the mean parameter. However, its standard deviation term is also statistically significant, indicating heterogeneity in preferences to avoid HABs within our sample of Lake Erie recreators. ${ }^{3}$

To further examine this underlying heterogeneity we estimate a latent class model. A membership function, which categories our Lake Erie visitors into different groups, must first be specified. Following Boxall and Adamowicz (2002), we first create a set of latent motivational constructs using responses from the 11 psychometric questions displayed in Figure [2] and factor analysis. Factor analysis allows us to distill the information gathered from these responses into a smaller set of determinants that can explain the underlying motivation for recreational site choice decisions on Lake Erie.

We recover four principal components from this analysis ${ }^{4}$ that summarize and account for the majority of variation present within these responses (Appendix Table [2]). We label the first component as "amenity preference" given the positive relationship between all the statements relating to site attributes and this factor; individuals in this segment tended to be more sensitive to differences in site-varying amenities than other lake visitors. The second component is called "recreational fishing quality" as the three primary determinants of this factor were: the presence of a boat ramp, fishing opportunities and the health of aquatic life. The third component, "shoreline amenities", differentiates recreators who were more interested in land-based amenities than water-related characteristics. Finally, our fourth factor, "aesthetic amenities", is characterized by people seeking nearby natural areas that are

[^2]peaceful and isolated from crowded areas. ${ }^{5}$

Factor scores were calculated for each individual and included, along with a vector of observable sociodemographics ${ }^{6}$, in the membership function (equation (5)). In order to determine the optimal number of population segments to be included within the latent class model, we estimated latent class models with 1-5 segments. We selected the model with the lowest Bayesian Information Criterion (BIC) score (the model with 2 segments) ${ }^{7}$ and present the results from its membership function in Table [5]. Notice the coefficients for the first group, "recreational fishermen", have been normalized to 0 . Consequently, the coefficients from the other segment, "beach-goers", must be described in relation to the fishermen segment. As is evident from Table [5], recreational fishermen are more likely to own a boating license, have a higher household income and have a lower education level than the average beach-goer. Most importantly, fishermen are significantly more concerned by the availability and quality of fishing at access points than beach-goers, which is depicted by the negative and statistically significant coefficient on Factor 2. The coefficients on the other principal components were statistically indifferent from 0 , indicating that the other three factors were not essential in differentiating beach-goers from the fishing group.

Two sets of utility parameters, one for each segment, were also estimated within the latent class

[^3]model. We present these results in Table [6]. ${ }^{8}$ The sign on both E. coli and algae continue to have the expected negative sign for both beach-goers and fishing enthusiasts. However, there is significant heterogeneity in willingness to avoid water pollution not only across groups but also across the type of water pollution present. In particular beach-goers tend to avoid areas where there are high concentrations of $E$. coli but are less concerned by the presence of harmful algae blooms. Recreational fishermen, however, tend to avoid algal-infested waters but were indifferent towards $E$. coli. This divergence in water quality preferences is likely due to the manner in which each population segment benefits from recreational amenities in fresh water lakes. Fishermen, on the one hand, may be more concerned about visibility issues that arise from recreating in algae-dense waters but are less concerned about the health side-effects associated with $E$. coli as they are not often directly interacting with the water. Beach-goers, on the other hand, are more likely to be wading and swimming in the water and therefore are potentially more sensitive and wary of $E$. coli, a well-known toxicogenic. ${ }^{9}$

Across the two groups of visitors, there is significant heterogeneity in preferences for non-water amenities as well. Beach-goers were more likely to visit access points that had a beach, picnic shelters and food stalls. Meanwhile fishermen tended to avoid areas with picnic shelters but sought out access points with boat ramps and restrooms. Similar to the parameters recovered from the conditional and

[^4]mixed logit models, both groups also preferred to recreate away from densely developed areas (i.e. Cleveland). Finally, there is significant heterogeneity in the travel cost parameter, with beach-goers being more averse to long distance locations than fishermen.

## V. Welfare

We further examine the welfare implications of the conditional and mixed logit estimates in Table [7]. We report marginal willingness to pay measures, which are calculated by dividing the estimated coefficients by the travel cost parameter, and use these estimates to recover welfare measures. According to the estimates from the conditional logit model, the welfare loss associated with an increase in algae is $\mathbf{-} \$ 0.14$ per 10,000 cells $/ \mathrm{mL}$. In other words, an increase of algae by 10,000 cells $/ \mathrm{mL}$ will lead to a welfare loss of 14 cents for a typical visitor. Considering the mean algae level at the recreational sites in our sample is 125,200 cells $/ \mathrm{mL}$, this reflects a cost of $\$ 1.75$ per visitor associated with the presence of the mean level of algae at a recreation site relative to a site with no algae. Using estimates from the mixed logit model, the willingness to pay to avoid algae increases to 21 cents per 10,000 cells $/ \mathrm{mL}$. At the mean algae concentration level this would represent a $\$ 2.63$ reduction in welfare per visitor. A similar pattern emerges when we estimate the impact of $E$. coli on recreator's well-being. A one-unit increase in E. coli $(1,000 \mathrm{cfu} / \mathrm{mL})$ reduces consumer welfare between $\$ 1.13$ and $\$ 2.04$, with the higher loss estimate derived from the conditional logit model. Evaluated at the average, observed E. coli level, this represents a total cost of between $\$ 2.03$ and $\$ 3.67$ per trip.

Finally, in our preferred latent class model specification, we find significant heterogeneity when we estimate separate water quality parameters for recreational fishermen and beach-goers. Fishermen are the most affected by algae-contaminated water, losing 41 cents per 10,000 cells/mL, while beach-goers
only lose 2 cents per 10,000 cells $/ \mathrm{mL}$. E. coli, on the other hand, is an important consideration for beach-goers, costing $\$ 1.10$ per $1,000 \mathrm{cfu} / \mathrm{mL}$. Recreational fishermen also appear to be sensitive to increasing concentrations of $E$. coli with a MWTP of $-\$ 3.32$ per $1,000 \mathrm{cfu} / \mathrm{mL}$. However, this value is derived from an insignificant estimate (see Table [6]) and is therefore statistically indifferent from 0.

In addition to marginal willingness to pay measures, it is also possible to exploit the structure of the discrete choice utility optimization problem and the estimated coefficients to calculate consumer surplus measures associated with non-marginal changes in lake quality. As climate change and increased urbanization will likely exacerbate water quality conditions over time, we develop several scenarios that focus on the potential welfare losses associated with worsening water quality. In addition, we also conduct a policy counterfactual that evaluate the welfare gains from a reduction in HABs. The first three scenarios involve changes to water quality for beach locations along the western shoreline of Lake Erie in Ohio ${ }^{10}$, which is an area that suffers from repeated exposure to HABs. The fourth scenario evaluates the implications associated with a lake-wide reduction in phosphorous as suggested by the 2012 GLWQA.

The four policies we evaluate include: 1) blue-green algae causing severe blooms in the western basin with algae levels reaching the highest levels recorded in Lake Erie (3,240,000 cells/mL in 2011); 2) closure of western sites due to algal blooms; 3) a prevention scenario where HABs are eliminated in the western basin; and 4) a targeted $40 \%$ reduction in lake-wide phosphorous loadings. These hypothetical scenarios provide insight into the potential welfare changes that would accrue to a typical day visitor to Lake Erie.

Welfare losses/gains associated with these simulations are presented in Table [8] for the conditional

[^5]logit, mixed logit and latent class models. Based on the conditional logit estimates, the average per-trip cost to a visitor would be $\$ 5.80$ when there are massive algae blooms in Lake Erie's western basin. For the mixed logit model, the costs are slightly lower with visitors losing $\$ 4.36$ per trip. The latent class specification reveals that fishing enthusiasts would be the most impacted by increases in algae, losing $\$ 16.96$ per trip, while beach-goers' welfare would drop by a modest $\$ 0.81$ per trip. If these western sites were closed due to algal blooms, the closures would cost $\$ 1.75$ per trip for beach-goers and $\$ 18.28$ per trip for recreational fishermen. In contrast, if harmful algal blooms were completely eliminated from Lake Erie's western basin, the benefit would be $\$ 0.15$ to $\$ 2.55$ per trip.

Aggregating these per-trip losses/gains across all Lake Erie trip-goers results in meaningful welfare measures for Ohio recreators. Following Murray et al. (2001) Palm-Forster et al. (2016), we estimate the annual number of trips to Lake Erie beaches in Ohio ( 6.25 million) by merging results from our survey with aggregate visitation data collected by the ODNR. ${ }^{11}$ Combining our valuation measures with this total day-trip estimate, and our predicted membership share from our latent class model, ${ }^{12}$ then allows us to recover group-specific welfare measures associated with non-marginal improvements or degradations in water quality. We find from this analysis that recreational fishermen and beach-goers would lose $\$ 59.2$ million and $\$ 5.3$ million respectively each year if all of the access points within Lake
${ }^{11}$ In 2010 the ODNR released estimates of annual visitation counts for each state park in Ohio. There were a total of seven state parks included within our choice set: Cleveland Lakefront, East Harbor, Geneva-on-the-Lake, Headlands Beach, Lake Erie Islands, Marblehead Lighthouse and Maumee Bay. Assuming 9.5\% of these trips were to the beach (Palm-Forster et al. 2016), we calculate the total number of day-trips to Lake Erie by dividing the number of beach visits for each site by the share of people who went to that location within our survey. Averaging across our seven locations gives us a value of 6.25 million trips.
${ }^{12}$ The probability of a visitor being a member of the beach-goer and the recreational fishermen segment is $51.8 \%$ and $48.2 \%$ respectively.

Erie's western basin were closed due to unsafe algae levels. Assuming there are approximately 90 days during the summer season, our aggregate losses closely resemble those recovered by Palm-Forster et al. (2016) when evaluating a 33 site closure along the western basin of Lake Erie. Specifically, they find aggregate daily loses to be between $\$ 573,730$ and $\$ 744,320$, which would be equivalent to $\$ 51,635,700$ and $\$ 66,988,800$ for a 90-day summer season.

Finally, we examine the gains attributed to a $40 \%$ reduction in lake-wide phosphorous loadings as suggested by the GLWQA. Using Stumpf and Wynne (2012)'s algae forecasting model ${ }^{13}$ we find this policy would reduce lake-wide algae by approximately $32 \%$, with western basin access points benefiting the most. ${ }^{14}$ On average, beach visitors would gain between $\$ 0.07$ per trip taken; however fishermen would be the biggest beneficiary, gaining $\$ 1.44$ per trip. Aggregating these values to an annual basis would result in gains of $\$ 4.3$ million and $\$ 227,000$ for recreational fishermen and beach-goers respectively.

## VI. Conclusions

Freshwater lakes provide important ecosystem services and recreational amenities. Poor water quality, due to the emergence and growth of harmful algal blooms caused by nutrient runoff, has been a growing concern in the Lake Erie region over the past two decades (Smith et al. 2015; Michalak et al 2013; Rinta-Kanto 2005;). A number of costly management solutions have been proposed in response to this environmental concern (Scavia et al. 2016; Sohngen et al. 2015), but to evaluate potential policies we

[^6]${ }^{14}$ Figure [3] depicts the absolute change in algae concentrations for each access point.
need reliable estimates of the benefits from water quality improvements. In this paper, we combine survey data with detailed geospatial information on water quality indicators - including algae and $E$. coli concentration - to estimate the recreational amenity benefits from water quality improvements to Lake Erie visitors. Using a random utility model we find Lake Erie recreational fishermen and beach-goers would lose $\$ 59.2$ million and $\$ 5.3$ million respectively each year if Lake Erie's western basin was closed due to severe algal blooms. The gains attributed to a $40 \%$ reduction in lake-wide phosphorous, on the other hand, are substantial but to a lesser extent with beach-goers and fishermen gaining \$227,000 and \$4.3 million respectively each year. While these benefits are considerable, they represent only a fraction of the true gains associated with a reduction in HABs as these benefits are capitalized in housing markets and recreational fishing patterns (Wolf and Klaiber 2017; Wolf et al. 2017). We further find heterogeneity in individual preferences towards lake shore amenities and disamenities including harmful algal blooms. Lake shore visitors' willingness to pay to avoid harmful algal blooms is significantly heterogeneous across our sample, with fishermen greatly benefiting from a reduction in algae concentration, while the welfare effects for beach-goers depend largely on reduction in E. coli.

Our analysis provides insights that are relevant for both local and regional policy decisions. Fresh water lakes provide a wide range of ecosystem services and recreational amenities that make regulations to address water quality a multi-jurisdictional concern. Whereas the provision of clean drinking water is a regional concern, amenities for beach visitors are local public goods. As there is no single approach to environmental concerns that span multiple spatial scales, policy response necessarily requires a cross-scale approach. As policy makers consider a suite of potential solutions to address water quality concerns in Great Lakes region in the U.S., this paper provides estimates of the potential welfare
implications of reductions in $E$. coli and HABs that can be used to determine the value of services provided and evaluate outcomes under different policy scenarios.

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Table 1: Respondents Characteristics

|  | Survey | Ohio Census | ODNR (2011) | U.S. Fish \& Wildlife (2011) |
| :---: | :---: | :---: | :---: | :---: |
| Male (\%) | 69.9 | 48.54 | 86 | 80 |
| White (\%) | 93.7 | 78.8 | - | 92 |
| Live in urban or suburban area (\%) | 80.9 | 87.18 | - | 63 |
| Married (\%) | 72.9 | 46.19 | - | - |
| Mean household size | 3.08 | 2.49 | - | - |
| Employed (\%) | 70.6 | 58.3 | 87.5 | - |
| Boating License (\%) | 24.4 | - | - | - |
| Fishing License (\%) | 41.0 | - | 100 | - |
| Mean household income (in 2016 dollars) | 79,690 | 67,991 | - | 51,940 |
| Some high school (\%) | 0.4 | 10.73 | 3.8 | 11 |
| High school graduate (\%) | 8.7 | 32.5 | 32 | 52 |
| Some college or associate's degree) (\%) | 26.2 | 31.65 | 34.1 | 17 |
| College graduate (\%) | 36.2 | 16.05 | 16.9 | 12 |
| Graduate or professional degree(\%) | 28.6 | 9.08 | 13.51 |  |

Notes: Census information for the 18 counties within our study region was gathered from the 2012-2016, 5 year ACS survey except for urban which came from the 2010 Census Summary File. Census estimates for \% are from a population of 15 years and older; similarily \% employed is gathered from a population of individuals 16 years and older, while educational attainment status is 18 years and over. The statistics collected from the ONDR survey only focus on the subsample of anglers who prefer to fish in Lake Erie. Finally, the US Fish and Wildlife Service survey does not distinguish between college graduates and individuals with graduate/professional degrees. The sum of these two categories is $12 \%$.

Table 2: Site Attribute ( $\mathrm{N}=106$ )

|  | Mean | Std | Min | Max |
| :--- | :---: | :---: | :---: | :---: |
| Beach (0/1) | 0.52 | 0.50 | - | - |
| Parking (0/1) | 0.85 | 0.36 | - | - |
| Boat ramp (0/1) | 0.30 | 0.46 | - | - |
| Restrooms (0/1) | 0.59 | 0.49 | - | - |
| Nature center (0/1) | 0.03 | 0.17 | - | - |
| Showers (0/1) | 0.17 | 0.38 | - | - |
| Trails (0/1) | 0.68 | 0.47 | - | - |
| Picnic area (0/1) | 0.58 | 0.50 | - | - |
| Food stands (0/1) | 0.21 | 0.41 | - | - |
| Playground (0/1) | 0.37 | 0.49 | - | - |
| Ecoli (1,000 cfu/mL) | 1.80 | 1.87 | 0.008 | 9.678 |
| Algae (10,000 cells/mL) | 12.52 | 22.41 | 1 | 97.56 |
| Distance to Cleveland (km) | 40.70 | 24.68 | 0.59 | 93.47 |
| Distance to Toledo (km) | 72.54 | 38.55 | 4.62 | 156.3 |
| Notes:Site-specific E.Coli values are measured by taking the maximum summer reading from the |  |  |  |  |

Notes: Site-specific E. Coli values are measured by taking the maximum summer reading from the closest monitoring location. Site-specific algae conditions are measured by taking the summer-long mean using only observations from the closest remote sensing location.

Table 3: Purpose of Trip and Calculated Travel Cost (N=549)

|  | Mean | Std | Min | Max |
| :--- | :---: | :---: | :---: | :---: |
| Travel cost (2016 Dollars) | 73.66 | 45.71 | 0.13 | 327.63 |
|  |  |  |  |  |
| Primary Purpose of Trip | 0.16 | 0.36 | - | - |
| Boating (0/1) | 0.10 | 0.30 | - | - |
| Swimming (0/1) | 0.06 | 0.25 | - | - |
| Sunbathing/beachcombing (0/1) | 0.06 | 0.24 | - | - |
| Fishing (0/1) | 0.12 | 0.33 | - | - |
| Wildlife watching/birding (0/1) | 0.23 | 0.42 | - | - |
| Participate in organized activity (0/1) | 0.12 | 0.32 | - | - |
| Walking/running (0/1) | 0.15 | 0.35 | - | - |
| Other/unknown (0/1) |  |  |  |  |

Notes: The participate in organized activity category includes activities such as going on a picnic, playing volleyball, having a bonfire, etc.

Table 4: Conditional and Mixed Logit

|  | Specification |  |  |
| :---: | :---: | :---: | :---: |
|  |  |  |  |
|  |  | Mean | SD |
| Travel cost (2016 Dollars) | $\begin{gathered} \hline-0.049 * * * \\ (0.003) \end{gathered}$ | $\begin{gathered} \hline-0.107^{* * *} \\ (0.012) \end{gathered}$ |  |
| E. coli (1,000 cfu/mL) | $\begin{gathered} -0.100^{* * *} \\ (0.026) \end{gathered}$ | $\begin{gathered} -0.121^{* * *} \\ (0.031) \end{gathered}$ | $\begin{gathered} 0.007 \\ (0.012) \end{gathered}$ |
| Algae (10,000 cells/mL) | $\begin{gathered} -0.007^{* *} \\ (0.003) \end{gathered}$ | $\begin{gathered} -0.023^{* * *} \\ (0.007) \end{gathered}$ | $\begin{gathered} 0.032^{* * *} \\ (0.008) \end{gathered}$ |
| Trail (0/1) | $\begin{aligned} & -0.089 \\ & (0.129) \end{aligned}$ | $\begin{aligned} & -0.050 \\ & (0.361) \end{aligned}$ | $\begin{gathered} 0.877 \\ (1.044) \end{gathered}$ |
| Picnic shelter (0/1) | $\begin{aligned} & 0.213^{*} \\ & (0.112) \end{aligned}$ | $\begin{gathered} 0.184 \\ (0.131) \end{gathered}$ | $\begin{gathered} 0.292 \\ (0.516) \end{gathered}$ |
| Food (0/1) | $\begin{gathered} 0.677^{* * *} \\ (0.120) \end{gathered}$ | $\begin{gathered} 0.683^{* * *} \\ (0.134) \end{gathered}$ | $\begin{gathered} 0.609 \\ (0.461) \end{gathered}$ |
| Shower (0/1) | $\begin{aligned} & 0.353^{*} \\ & (0.125) \end{aligned}$ | $\begin{gathered} 0.423^{* * *} \\ (0.134) \end{gathered}$ | $\begin{gathered} 0.084 \\ (0.218) \end{gathered}$ |
| Boat ramp (0/1) | $\begin{gathered} -0.290^{* *} \\ (0.101) \end{gathered}$ | $\begin{gathered} -0.356^{* * *} \\ (0.131) \end{gathered}$ | $\begin{gathered} 0.664 \\ (0.429) \end{gathered}$ |
| Restrooms (0/1) | $\begin{gathered} 0.691^{* * *} \\ (0.154) \end{gathered}$ | $\begin{gathered} 5.619 \\ (3.689) \end{gathered}$ | $\begin{aligned} & 7.212^{*} \\ & (4.187) \end{aligned}$ |
| Beach (0/1) | $\begin{gathered} 0.272^{* *} \\ (0.114) \end{gathered}$ | $\begin{gathered} 0.360^{* * *} \\ (0.138) \end{gathered}$ | $\begin{gathered} 0.277 \\ (0.741) \end{gathered}$ |
| Distance to Cleveland (km) | $\begin{gathered} 0.014^{* * *} \\ (0.003) \end{gathered}$ | $\begin{gathered} 0.009 \\ (0.006) \end{gathered}$ | $\begin{gathered} 0.011 \\ (0.008) \end{gathered}$ |
| Distance to Toledo (km) | $\begin{gathered} -0.009 * * * \\ (0.002) \end{gathered}$ | $\begin{gathered} -0.017^{* * *} \\ (0.005) \end{gathered}$ | $\begin{gathered} 0.087^{* * *} \\ (0.012) \end{gathered}$ |
| Sample Size | 549 |  |  |

Notes: ${ }^{*},{ }^{* *},{ }^{* * *}$ represent significance at the $10 \%, 5 \%$ and $1 \%$ level respectively. Robust standard errors have been clustered at the individual level.

Table 5: Membership Function

|  | Beach-Goers | Recreational Fishermen |
| :---: | :---: | :---: |
| Factor 1-Amenity Preferences | -0.044 | 0 |
|  | (0.076) |  |
| Factor 2 - Recreational Fishing Quality | -0.323*** | 0 |
|  | (0.110) |  |
| Factor 3 - Shoreline Amenities | -0.006 | 0 |
|  | (0.106) |  |
| Factor 4 - Aesthetic Amenities | 0.134 | 0 |
|  | (0.124) |  |
| Income (2016 Dollars) | -0.165*** | 0 |
|  | (0.045) |  |
| Boat License (0/1) | -0.574* | 0 |
|  | (0.341) |  |
| Education | 0.490* | 0 |
|  | (0.293) |  |
| Male (0/1) | -0.169 | 0 |
|  | (0.284) |  |
| Employed (0/1) | 0.303 | 0 |
|  | (0.295) |  |
| Intercept | 1.067*** | 0 |
|  | (0.391) |  |

Notes: ${ }^{*},{ }^{* *},{ }^{* * *}$ represent significance at the $10 \%, 5 \%$ and $1 \%$ level respectively. Robust standard errors have been clustered at the individual level.

Table 6: Latent Class Model

|  | Beach-Goers | Recreational Fishermen |
| :---: | :---: | :---: |
| Travel cost (2016 Dollars) | -0.206*** | -0.0234*** |
|  | (0.0242) | (0.00296) |
| E. coli (1,000 cfu/mL) | -0.227*** | -0.0778 |
|  | (0.0740) | (0.0521) |
| Algae (10,000 cells/mL) | -0.00402 | -0.00967** |
|  | (0.00852) | (0.00492) |
| Trail (0/1) | 0.273 | -0.260 |
|  | (0.330) | (0.176) |
| Picnic shelter (0/1) | 0.882*** | -0.357* |
|  | (0.290) | (0.213) |
| Food (0/1) | 1.095*** | 0.236 |
|  | (0.245) | (0.268) |
| Shower (0/1) | 0.326 | 0.461* |
|  | (0.228) | (0.278) |
| Boat ramp (0/1) | -1.159*** | 0.445*** |
|  | (0.268) | (0.169) |
| Restrooms (0/1) | -0.299 | 0.997*** |
|  | (0.382) | (0.212) |
| Beach (0/1) | 1.092*** | -0.175 |
|  | (0.234) | (0.189) |
| Distance to Cleveland (kr | 0.0270* | 0.0184*** |
|  | (0.0152) | (0.00451) |
| Distance to Toledo (km) | 0.0317** | -0.00441 |
|  | (0.0152) | (0.00275) |

Sample Size 492
Notes: *, **, *** represent significance at the 10\%, 5\% and 1\% level respectively. Robust standard errors have been clustered at the individual level.

Table 7: Marginal Willingness to Pay

|  | Conditional <br> Logit | Mixed Logit | Latent Class |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Beach-Goers |  |  |  |
| E. coli $(1,000$ cfu $/ \mathrm{mL})$ | -2.04 | -1.13 | -1.1 | -3.32 |
| Algae $(10,000$ cells $/ \mathrm{mL})$ | -0.14 | -0.21 | -0.02 | -0.41 |
| Trail $(0 / 1)$ | -1.82 | -0.47 | 1.33 | -11.11 |
| Picnic shelter (0/1) | 4.35 | 1.72 | 4.28 | -15.26 |
| Food (0/1) | 13.82 | 6.38 | 5.32 | 10.09 |
| Shower (0/1) | 7.20 | 3.95 | 1.58 | 19.7 |
| Boat ramp (0/1) | -5.92 | -3.33 | -5.63 | 19.02 |
| Restrooms (0/1) | 14.10 | 52.51 | -1.45 | 42.61 |
| Beach (0/1) | 5.55 | 3.36 | 5.3 | -7.48 |
| Distance to Cleveland (kr | 0.29 | 0.08 | 0.13 | 0.79 |
| Distance to Toledo $(\mathrm{km})$ | -0.18 | -0.16 | 0.15 | -0.19 |

Note: All estimates are measured in 2016 dollars.

Table 8. Welfare Implications of Algal Changes (Per-Trip)

|  | Affected Region | Conditional Logit | Mixed Logit | Latent Class |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | Recreational Fishermen |  |
| Algae Bloom | Western Basin | -5.80 | -4.36 | -0.81 | -16.96 |
| Site Closures | Western Basin | -7.67 | -4.51 | -1.75 | -1.28 |
| No Algae | Western Basin | 1.00 | 1.43 | 0.15 | 0.55 |
| $40 \%$ reduction in spring phosphorous loadings | Lakewide | 0.47 | 0.57 | 0.07 | 1.44 |

Note: All estimates are measured in 2016 dollars.

Figure 1: Sampled Counties and Mailing Addresses


Figure 2: Importance of Site Characteristics


Figure 3: Absolute Change in Algae Concentrations Due to a $40 \%$ Reduction in Phosphorous Loadings


Absolute change in algal concentrations (10,000 cells $/ \mathrm{mL}$ )


Appendix Table 1: Mixed Logit with Opt-out Option

|  | Mean | SD |
| :---: | :---: | :---: |
| Travel cost (2016 Dollars) | -0.057*** | -- |
|  | (0.004) | -- |
| Home (0/1) | 1.112*** | -- |
|  | (0.342) | -- |
| E. coli (1,000 cfu/mL) | -0.086*** | 0.004 |
|  | (0.032) | (0.051) |
| Algae (10,000 cells/mL) | -0.018*** | 0.024*** |
|  | (0.007) | (0.008) |
| Trail (0/1) | 0.290 | 2.183** |
|  | (0.314) | (1.004) |
| Picnic shelter (0/1) | 0.193 | 0.042 |
|  | (0.132) | (0.435) |
| Food (0/1) | 0.643*** | 0.157 |
|  | (0.138) | (0.336) |
| Shower (0/1) | 0.371** | 0.273 |
|  | (0.144) | (0.322) |
| Boat ramp (0/1) | -0.291** | 0.477 |
|  | (0.138) | (0.429) |
| Restrooms (0/1) | 0.705*** | 0.345 |
|  | (0.164) | (0.675) |
| Beach (0/1) | 0.326*** | 0.248 |
|  | (0.122) | (0.362) |
| Distance to Cleveland (km) | 0.008* | 0.041*** |
|  | (0.004) | (0.006) |
| Distance to Toledo (km) | -0.008*** | 0.000 |
|  | (0.002) | (0.004) |
| Sample Size | 738 |  |
| Notes: *, **, *** represent significance at the 10\%, 5\% and $1 \%$ level respectively. Robust standard errors have been clustered at the individual level. The home variable is a $0-1$ indicator, with 1 indicating the individual recreated in Lake Erie during the summer of 2016 and 0 indicating otherwise. |  |  |

Appendix Table 2: Factor Analysis

|  | Factor Loadings |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
| Statement | Factor 1 <br> (Amenity Preferences) | Factor 2 <br> (Recreational <br> Fishing Quality) | Factor 3 <br> (Shoreline <br> Amenities) | Factor 4 <br> (Aesthetic <br> Amenities) |
| Presence of boat ramp | 0.2194 | 0.5825 | 0.1988 | -0.0839 |
| Fishing opportunity available | 0.2124 | 0.6120 | 0.1367 | 0.0173 |
| Convenient facilities nearby | 0.3571 | -0.1161 | 0.3357 | -0.1154 |
| Nature area nearby | 0.3265 | -0.0424 | -0.0990 | 0.6266 |
| Not crowded | 0.2742 | -0.0740 | 0.2884 | 0.3229 |
| Sandy (rather than rocky) beach | 0.2099 | -0.2672 | 0.4556 | -0.2770 |
| Convenient parking available | 0.2596 | -0.2017 | 0.3751 | 0.0012 |
| The health of aquatic life | 0.3514 | 0.2219 | -0.3488 | 0.0851 |
| The odor of the water | 0.3563 | -0.0918 | -0.3319 | -0.4188 |
| The water clarity of the water | 0.3892 | -0.0839 | -0.3027 | -0.3716 |
| Scenic beauty or nice view | 0.2900 | -0.2977 | -0.2540 | 0.2917 |

Appendix Table 3 - Latent Class Model without Sociodemographics in Membership Function

|  | Beach-Goers | Recreational Fishermen |
| :--- | :---: | :---: |
| Travel cost (2016 Dollars) | $-0.208^{* * *}$ | $-0.023^{* * *}$ |
|  | $(0.026)$ | $(0.003)$ |
| E. coli (1,000 cfu/mL) | $-0.236^{* * *}$ | -0.074 |
| Algae (10,000 cells/mL) | $(0.076)$ | $(0.052)$ |
|  | -0.003 | $-0.010^{* *}$ |
| Trail (0/1) | $(0.009)$ | $(0.005)$ |
|  | 0.281 | -0.260 |
| Picnic shelter (0/1) | $(0.347)$ | $(0.177)$ |
|  | $0.844^{* * *}$ | -0.322 |
| Food (0/1) | $(0.283)$ | $(0.213)$ |
|  | $1.079^{* * *}$ | 0.256 |
| Shower (0/1) | $(0.239)$ | $(0.272)$ |
|  | $0.375^{*}$ | 0.403 |
| Boat ramp (0/1) | $(0.227)$ | $(0.282)$ |
|  | $-1.073^{* * *}$ | $0.403^{* *}$ |
| Restrooms (0/1) | $(0.252)$ | $(0.169)$ |
| Beach (0/1) | -0.291 | $0.988^{* * *}$ |
|  | $(0.381)$ | $(0.213)$ |
| Distance to Cleveland (kn | $1.139^{* * *}$ | -0.208 |
| Distance to Toledo (km) | $(0.246)$ | $(0.190)$ |
|  | 0.0234 | $0.019^{* * *}$ |
|  | $(0.016)$ | $(0.004)$ |
|  | -0.004 |  |
|  |  | $(0.003)$ |
|  | 492 |  |

Notes: *, ${ }^{* *}$, ${ }^{* * *}$ represent significance at the 10\%, 5\% and 1\% level respectively. Robust standard errors have been clustered at the individual level.

Appendix Table 4 - Summary Statistics for the Latent Class Subsample and for the Full Survey

|  | Full Survey <br> $(\mathrm{N}=738)$ | Latent Class Model <br> $(\mathrm{N}=492)$ |
| :--- | :---: | :---: |
| Male (\%) | 68.2 | 70.4 |
| White (\%) | 92.9 | 93.6 |
| Live in urban or suburban area (\%) | 80.1 | 80.9 |
| Married (\%) | 72.3 | 72.6 |
| Mean household size | 3.05 | 3.12 |
| Employed (\%) | 69.5 | 72.3 |
| Boat License (\%) | 23.0 | 23.8 |
| Fish License (\%) | 37.5 | 39.5 |
| Median household income (in 2016 dollars) | 75,000 | 75,000 |
| Mean household income (in 2016 dollars) | 77,888 | 80,311 |
| Some high school (\%) | 0.4 | 0.4 |
| High school graduate (\%) | 9.6 | 8.3 |
| Some college or associate's degree) (\%) | 26.8 | 25.6 |
| College graduate (\%) | 36 | 36 |
| Graduate or professional degree(\%) | 27.1 | 29.7 |

Notes: We dropped 11 observations from the full sample due to respondents not fully understanding all of the survey questions, indicating they recreated outside of Ohio or finished the survey too quickly (<2 minutes) or too slow (>3 hours).


[^0]:    ${ }^{1}$ Missing income values were assigned census tract-level, median annual household income from the American Community Survey.

[^1]:    ${ }^{2}$ We treat the coefficient on travel cost as constant across individuals and groups to aid in welfare interpretation.

[^2]:    ${ }^{3}$ In addition to estimating a standard mixed logit model, we also tested, for robustness, a mixed logit model with an opt-out option of whether or not the respondent went to Lake Erie at all during the summer of 2016. Results from this modified specification/sample are presented in Appendix Table [1].
    ${ }^{4}$ Similar to Boxall and Adamowicz (2002) we recover components using principal component analysis. Components with eigenvalues less than 1 were omitted from the membership function.

[^3]:    ${ }^{5}$ Results from this factor analysis are displayed in Appendix Table [2].
    ${ }^{6}$ Our findings are robust to the exclusion of sociodemographics within the membership function (see Appendix Table [3] for results).
    ${ }^{7}$ The BIC score for the two-segment model is 3645.02 .

[^4]:    ${ }^{8}$ Note the sample size in the latent class model decreases to 492 due to missing survey-takers not responding to all of the socioeconomic/qualitative questions. We present a summary stats table for this sub-sample, along with the entire sample of Lake Erie recreators/non-recreators, in Appendix Table [4].
    ${ }^{9}$ Relative to recreational fishermen, beach-goers were found to be less responsive to harmful algal blooms, suggesting a disconnect exists between the public's perception of recreating in algae-contaminated water and the actual risk associated with ingesting or coming into contact with HABs. A similar finding was observed within a housing market setting (Wolf and Klaiber 2017). In particular, housing values were found to be unresponsive to algae-induced water quality degradation after a no-drinking advisory threshold was already surpassed.

[^5]:    ${ }^{10}$ Specifically, this includes sites located in either Erie, Lucas or Ottawa county.

[^6]:    ${ }^{13}$ Stumpf et al (2012) use June phosphorous readings collected between 2002 and 2010 to create their HAB forecasting model. We mirror this approach when defining a current, average phosphorous loadings value.

