Valuing Recreational Angling Loss from Harmful Algal Blooms in Lake Erie

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Abstract

Despite increasing public awareness of harmful algal blooms (HABs) in the United States and overseas, few previous studies have examined how HABs affect recreational angling trip behavior from season to season, where variation in HABs can be driven by the interaction of anthropogenic drivers, like nutrient emissions, with non-anthropogenic drivers like weather and climate. This research combines revealed preference data on Lake Erie fishing locations from 2011 to 2018. We construct a zonal dataset by linking 20-minute boat counts at 36 major harbor sites in Ohio, as well as angler survey data with zip codes for randomly selected anglers. We estimate anglers' site choice decisions with a nested logit model where people choose whether to go on a trip in Lake Erie, and which site they choose if they take a trip. The model includes a full set of time-invariant fixed effects for each site along with a measure of HAB severity that varies by time and site. Results indicate that the probability of making a trip to sites on Lake Erie decreases as HABs increase.

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Introduction

Fishing has long been a popular outdoor activity in the world, particularly in the United States. In 2020, around 55 million Americans visited the country's waterways to participate in freshwater and saltwater activities. The number is expected to rise in the future and can benefit the health and wellbeing of millions of all ages (Statista Research Department, 2022). In addition to being an outdoor recreation activity for residents, fishing can be considered a form of tourism when anglers travel to go fishing (US Department of Commerce, 2021). Anglers spend money locally on tackle, hotel, restaurant, boat and equipment rentals, fishing guides, and more. Lake Erie is the fourth-largest lake (by surface area) of the five Great Lakes in North America and the eleventh largest globally. Its fish population accounts for an estimated 50% of all fish inhabiting the Great Lakes. Well-known as “The Walleye Capital of the World”, Lake Erie is home to a $1.5 billion sport fishing industry for over two million anglers (Lucente et al., 2012).

Harmful algal blooms (HABs) are diverse phenomena when algae—simple photosynthetic organisms that live in the sea and freshwater—grow out of control while producing toxins which can cause acute or chronic health effects in mammals (including humans) and other organisms (Carmichael and Boyer, 2016; Hudnell, 2010). The U.S. national HAB problem is far more extensive than it was decades ago, with more toxic species and toxins to monitor, as well as a larger range of impacted resources and affected areas (Anderson et al., 2021). Lake Erie has been under threat of increasing HABs since 1960s, which occur when phosphorus levels are high within the lake. Recently, HABs have been increasing in extent and intensity in the western basin of Lake Erie, mainly due to crop and livestock production in upstream agricultural watersheds (Michalak et al., 2013). National Oceanic and Atmospheric Administration (NOAA) has reported unsafe toxin concentrations in Lake Erie and has since advised people (and their pets) to stay away from areas where scum is forming on the water surface.

A large body of literature has been devoted to evaluating loss or gains of recreational uses from environmental quality changes (Bockstael et al., 1987; Cicchetti et al., 1976; Dundas and von Haefen, 2020; English et al., 2019; Fisher et al., 1972; von Haefen and Lupi, 2021). Many studies have analyzed the recreational choices among mutually exclusive site alternatives with random utility theory, which assumes that rational recreators maximize their utilities when making choices (Parsons et al., 1999; von Haefen, 2003; Wallentin, 2016). Multinomial logit, conditional logit, and their more general versions mixed logit and nested logit models are commonly used to estimate the parameters of characteristics of alternatives like prices and amenities (Cheng and Lupi, 2016; Heiss, 2002; Kling and Thomson, 1996; von Haefen and Phaneuf, 2003).

Most current research on recreational choices is based on mail survey data, including recall of people's past recreational experiences or stated preference in hypothetical choice experiments (Hanemann, 1984; Rakotonarivo et al., 2016; Zhang and Sohngen, 2018). Recently, some studies combine the revealed preference data and stated preference data by doing on-site interval surveys and follow-up surveys of hypothetical choice experiments (Boudreaux et al., 2023; Cheng and Lupi, 2016). Few of them use on-site revealed preference data only, which helps avoid the problem of recall bias, especially in a long term (Friedenreich et al., 2006; Rakotonarivo et al., 2016) as well as hypothetical bias under hypothetical situations (List and Gallet, 2001; Murphy and Stevens, 2004; Loomis, 2014). However, a prominent problem of using revealed preference data is how to deal with choices in a longer term, such as a recreational season or a year, when some recreators' demand is positive while others is zero (choose non-trip option) during some time because only the goers can be intercepted on site (Haab and McConnell, 2002). Some studies ignore people who choose not to recreate due to their absence on site (Morey et al., 1993; Phaneuf and Smith, 2005). One solution is to link the site choice with the quantity of trips using repeated logit model, in which the recreator is assumed to have a fixed number of choice occasions, and for each occasion chooses whether to recreate and then, conditional on choosing to recreate, picks the site (Morey et al., 1993).

Many studies have examined factors impacting recreational activities in Lake Erie, such as water quality advisories or warnings (Boudreaux, 2021; Murray et al., 2001), perceived water quality (Cheng and Lupi, 2016; Phaneuf et al., 1998), and beach closures (Palm-Forster et al., 2016; Parsons et al., 1999). Only three studies have estimated the impacts of HABs, however, likely due to the limited availability of the HAB data. A report suggests a negative relationship between HABs and recreational fishing trips in Lake Erie based on yearly aggregate summary statistics (Environmental Consulting & Technology, Inc., 2015). Zhang and Sohngen (2018) estimate anglers' willingness to pay to avoid HABs by doing a discrete choice experiment in a mail survey, and find that Ohio anglers are on average willing to pay \$8 to \$10 for one less mile of HAB to boat through before reaching the desired fishing site. Wolf et al. (2019) use mail survey data and a latent-class framework to examine the effects of HABs and E. coli events simultaneously on both beach users and anglers in Lake Erie, and find that the welfare loss associated with an increase in algae is \$0.25 per 10,000 Microcystis cells/ml. In summary, few previous studies have examined how trip behavior changes from year to year, where variation in HABs can be driven by the interaction of anthropogenic drivers, like nutrient emissions, with non-anthropogenic drivers like weather and climate. There is also a lack of more accurate estimation of the loss of recreational angling trips from HABs in Lake Erie taking non-trip option into consideration.

In this study, anglers' site choice decisions are estimated with a nested logit model where people choose whether to go on a trip in Lake Erie, and the site that yields the highest utility conditional on choosing to go. We use revealed preference data from 2011 to 2018, which are obtained from the Ohio Department of Natural Resources (ODNR) annual creel survey of Lake Erie anglers, including 20-minute boat counts at 36 major harbor sites in Ohio, as well as interview data with randomly selected anglers to provide zip code data for random utility model (RUM) analysis.

In this paper, we make three contributions to the literature: first, we construct a unique zonal dataset where we treat each zip code as a representative agent who makes trip decisions; second, we link every interviewee with a weight equal to the inverse probability of being intercepted using the stratified random sampling setting of the data, which helps to reflect the overall recreation demand; and third, we use the on-site revealed preference data to explore the impacts of HABs, which helps to avoid recall bias and hypothetical bias. This paper adds to our understanding about how recreational anglers avert HABs, and how many trips and how much welfare would be lost because of HABs. The results could help fishery managers to allocate limited funds between HAB reduction and other projects. Furthermore, it could help policymakers to understand the value of natural resources, which could contribute to a more comprehensive evaluation of pollution regulations and abatement programs.

Data

This study focuses on the implications of HABs on the recreational fishing demand in 36 major harbor sites along Ohio's portion of the Lake Erie shoreline shown in Figure 1. We group the sites into 16 groups based on the locations. The boat counts in 20-minute intervals are gathered from the Ohio Department of Natural Resources - Division of Wildlife (ODNR-DOW) annual creel surveys during 2011-2018 (ODNR-DOW, 2019). Creel survey sites are typically surveyed during 3 weekdays and 2 weekend days each week from April to October. The dates and interview schedules are randomly selected within this schema, stratified by day of the week.

Figure 2 shows the mean private boat counts in 20 min across years and basins for weekdays and weekends. We divide the sample into weekdays and weekends because the counts on weekdays are relatively smaller and stabler while those on weekends are relatively higher and more liable across years. Substantial heterogeneity across years exists. On both weekdays and weekends, the boat counts in the western basin and central basin tend to move in the same direction, which is opposite to the eastern basin. This can serve as evidence that when anglers make recreation site choices, substitution effect among sites might exist.

During the 20-minute count intervals, survey staff also try to find one spokesman of each boat and try to interview as many spokesmen on the counted boats as possible. Interviews identify the spokesman’s zip code, the type of fishery (private or charter), and the number of anglers on the boat.

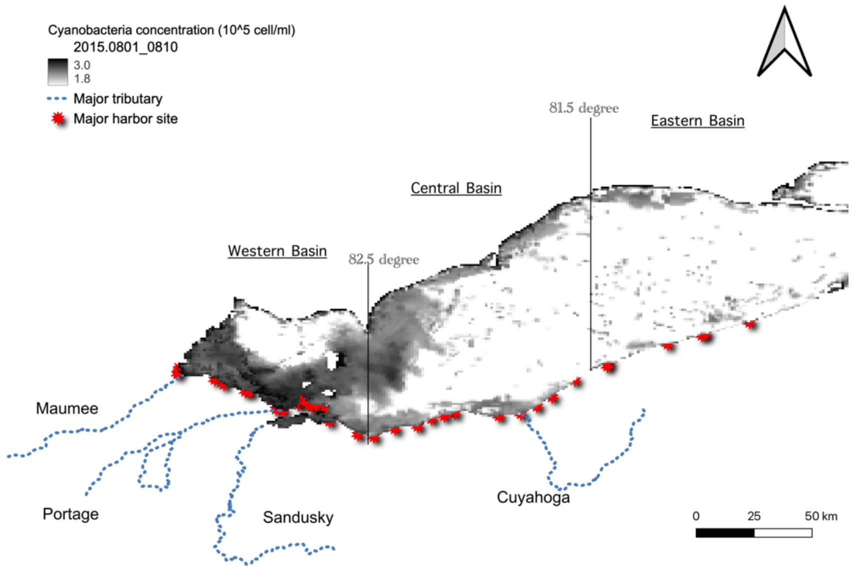

Figure 1 Location of major harbor sites along Lake Erie coast in Ohio

Notes: The algal-composite raster image of 2015-08-01 to 2015-08-10 is shown in the area of Lake Erie, with darker color corresponding to higher concentration levels of cyanobacteria.

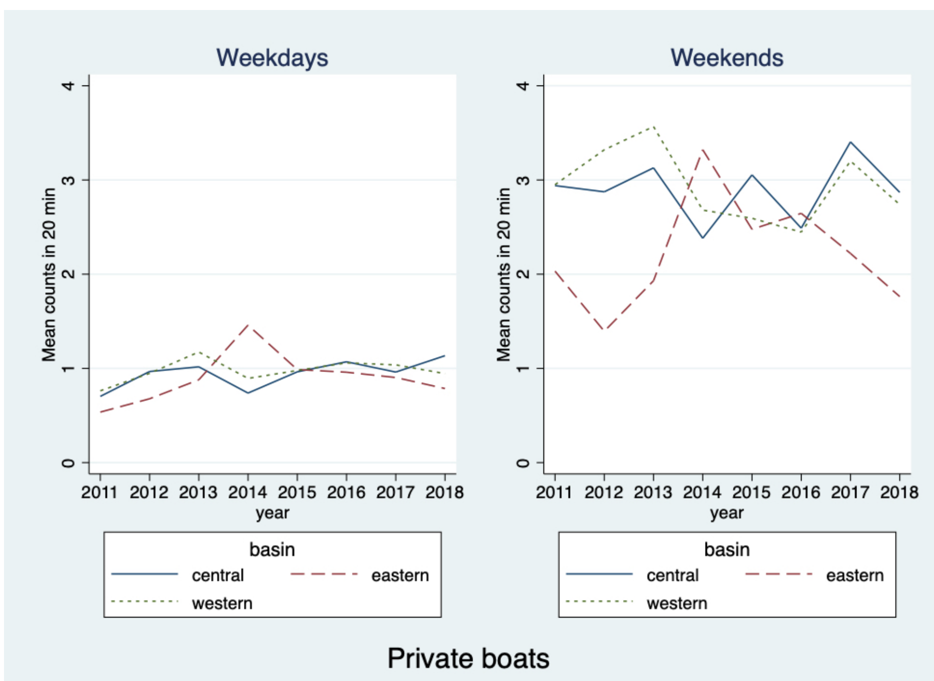

Figure 2 Mean private boat counts in 20 min across years and basins for weekdays and weekends

In addition to boat counts and angler information, we acquire the 10-day algal-composite data of the Great Lakes during 2011-2018 from the NOAA (Stumpf et al., 2016; Wynne and Stumpf, 2015). Lake Erie HAB raster images are available only for the summer and fall months (June to October) in part due to low or undetectable levels of cyanobacteria present during much of the winter and spring. The satellite datasets are at each map pixel of about 1100 by 1100 m from the individual scenes within sequential (non-overlapping) 10-day periods.

We use the mean concentration of cyanobacteria within 3 miles of each harbor site in each 10-day interval. Mean concentrations of cyanobacteria over time and basins are shown in Figure 3. Two observations are evident from this figure. First, 2011, 2014, and 2015 experienced severe HABs which is consistent with the record from NCCOS[1]. Second, HABs most frequently occur in the western basin and are less frequent in the central and eastern basins, which is due to most of the soluble reactive Phosphorus that drives HABs entering the Lake from the western basin through tributaries like Maumee River (Berardo et al., 2019).

[1] https://glisa.umich.edu/resources-tools/climate-impacts/algal-blooms/#:~:text=The%20most%20recent%20significant%20algal,(severity%20index%20of%2010.5).

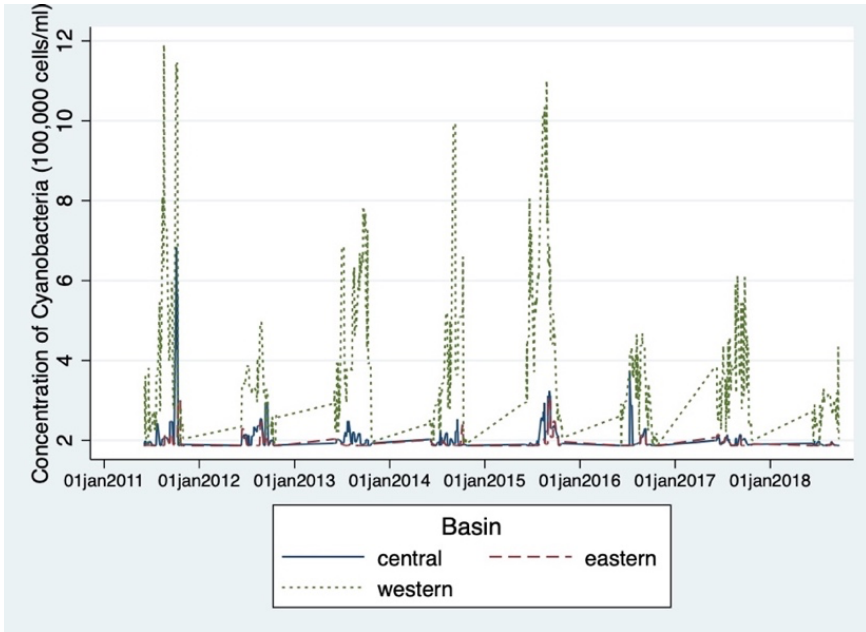

Figure 3 Mean Concentration of Cyanobacteria (100,000 cells/ml) within 3 miles of each site across time and basin

To form travel costs, we assemble temporally and spatially varying variables from multiple datasets and follow recommendations of Lupi et al. (2020). First, we obtain weekly Midwest regular conventional retail gasoline prices from the U.S. Energy Information Administration (EIA, 2023). We then calculate the CPI-adjusted gas prices calculated by the weekly gas prices over monthly Core Inflation Rates from the U.S. Inflation Calculator (US Inflation Calculator, 2023). Second, we obtain miles per gallon (MPG), maintenance costs, and marginal depreciation costs for each vehicle type from the annual AAA Your Driving Costs Report for 15,000 miles driven each year (AAA, 2019). Then we calculate per-mile driving cost by summing up gasoline costs, maintenance costs, and marginal depreciation costs with a weighted average of costs across vehicle types (Lupi and von Haefen, 2021). Third, to compute the travel time (in minutes) and distance (in miles) by driving between the centroid of each origin zip code and each site, we use mqtime, a STATA tool with MapQuest web service (Weber and Péclat, 2017). The travel distance and time to each site are calculated by the mean number to each location in the site. Fourth, we gather demographic statistics including median annual income, median age, the percentage of people with a bachelor's degree or higher, the percentage of White people, and the unemployment rate for each zip code from the American Community Survey's 2015-2019 five-year estimates from the US Census Bureau (US Census Bureau, 2020).

Methodology

Zonal dataset construction

Since anglers' personal characteristics (e.g., income, gender, age, education) cannot be identified in the survey, we treat each zip code as a representative agent and construct a zonal dataset by linking boat counts data and angler survey data following the approach of von Haefen et al.(2019).

First, we estimate the total number of boat trips $\widehat{C_{jhy}}$ at site j at each stratum of year, month, and weekdays or weekends using the sampled boat counts c_{jmdy} at site j on day d, month m, year y:

$$\widehat{C_{jhy}} = N_{hy} * \frac{M_{hy} * 60\ min}{20\ min} \frac{\sum_{md\epsilon h} c_{jmdy}}{n_{jhy}}$$

where h is a vector indicating stratum consisting of month and weekdays or weekends, c_{jmdy} is the returning count of boats at site j on day d, month m, year y, N_{hy} is the total number of days in stratum h in year y, M_{hy} is the average day length over stratum h in year y, in hours, n_{jhy} is the total number of days in stratum h that sampled site j in year y.

Second, I link boat counts data with angler survey data to examine site choice decisions on individual level. Following Leggett (2017) and Tourangeau et al. (2017), I assign angler i intercepted at site j in stratum h in year y a weight so that the sum of the weights of all interviewees equals the sum of boat counts estimated:

$$w_{ijhy} = \frac{\widehat{C_{jhy}}}{I_{jhy}}$$

where I_{jhy} is the number of anglers interviewed at site j over stratum h in year y. The estimate boat counts $\widehat{C_{jhy}}$ are equally divided to I_{jhy} anglers. Once w_{ijhy} is obtained for every intercepted angler, I sum these weights over all anglers from same zip code *z* interviewed at site *j* over stratum *h* in year *y* to recover an estimate of the total visitation from each zip code to each site in each stratum:

$$w_{zjhy} = \sum\nolimits_{zj} w_{ijhy}$$

Next, I sum up the weights of all anglers from the same zip code *z* interviewed at site *j* for the zip code agent in year *y* across all stratum *h*:

$$w_{zjy} = \sum\nolimits_{h} w_{zjhy}$$

For each origin zip-code representative, $\widehat{T_{zy}}$ is the number of trips from zip code *z* in year *y*:

$$\widehat{T_{zy}} = \sum_j w_{zjy}$$

Following von Haefen et al (2019) and von Haefen and Domanski (2018), I construct $\widehat{T_{zy0}}$, the number of times in zip *z* that choices other than recreational angling trips in Lake Erie (non-trip choice) were chosen in each year, using $\widehat{T_{zy}}$ and the total population of *z* pop_z:

$$\widehat{T_{zy0}} = A * pop_z - \widehat{T_{zy}}$$

$$A = \max_{z \in Z} \left\{ 1.1 * \frac{\widehat{T_{zy}}}{pop_z} \right\}$$

where *Z* is the set of all zip code *z* and *A* is a scaling factor which ensures that the number of choice occasions for each zip code can never be less than the number of estimated visits and is always at least 10% larger.

Site choice model

The site choice model is rooted in RUM theory and uses the zonal dataset to model the recreation decision process in a two-level nested logit framework with weights. On each choice occasion, zip code representative agents decide whether to make an angling trip to Lake Erie or not, and, conditional on taking an angling trip, they choose the site that yields the most utility out of all the available 16 sites. Figure 4 illustrates the nests within the site choice model, where the site nest alternatives may have errors that are more correlated with one another than with the "no-trip" alternative.

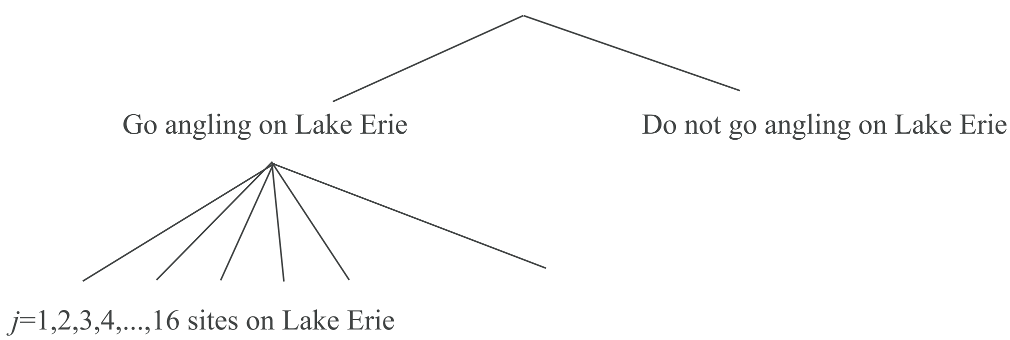

Figure 4. Nesting Structure of Site Choice Model

The probability of zip-code representative *z* choosing alternative *j* is equal to the product of the probability to choose some alternative in nest *B(j)* and the conditional probability to choose exactly alternative *j* given some alternative in the same nest *B(j)* is chosen:

$$P_j = Pr(choice = j) = Pr\{choice = j | choice \in B(j)\} \cdot Pr\{choice \in B(j)\}$$

where the individual subscript *z* is dropped from now on for the sake of a more concise notation, *choice* is the choice of any alternative, *B(j)* is the nest *j* belongs to. For each nest *l=1,2*, the joint distribution of the error terms has an additional parameter τ_l that represents a measure of the mutual correlation of the error terms of all alternatives within this nest. This paper specifies τ_l to be equal to $\sqrt{1-\rho_l}$, with ρ_l representing the correlation coefficient, which is often called dissimilarity parameter. According to Heiss (2002), the equation could then be revised to:

$$Pr\{choice = j | choice \in B(j)\} = \frac{exp\left(V_j/\tau(j)\right)}{\sum_{alt \in B(j)} exp\left(V_{alt}/\tau(j)\right)} \tag{13}$$

where alt represents any alternative in nest $B(j)$.

Following Boudreaux (2021), the conditional indirect utility a zip code representative agent z receives from choosing the non-trip option (site 17) is assumed to be composed of an observable representative utility component and a random unobservable error term:

$$U_{z0} = V_{z0} + \varepsilon_{z0}$$

$$= \beta_{inc}\ med.income_z + \beta_{age}\ med.age_z + \beta_{bach}\ \%\ bachelor_z + \beta_{white}\ \%\ white_z$$

$$+\beta_{unemployed}\ \%\ unemployed_z + \varepsilon_{z0}$$

The conditional indirect utility z receives from choosing site $j \neq 17$ is also composed of representative utility and a random error term, where the representative utility term is specified as a function of travel cost and HABs as below:

$$U_{zjy} = V_{zjy} + \varepsilon_{zjy} = \beta_{TC} TC_{zjy} + \beta_{HAB} HAB_{jy} + \alpha_j + \varepsilon_{zjy} \tag{15}$$

where α_j is an alternative-specific constant (ASC), a site-level fixed effect that captures the influence of site-specific characteristics omitted from the utility function.

I construct the round-trip travel cost for each zip-site combination in each individual choice set accounting for per-mile driving costs as well as the opportunity cost of time:

$$TC_{zjy} = distance_{zj} * cost\ per\ mile_y + time_{zj} * 0.4 * \left(\frac{median\ income_{zy}}{2000}\right) \tag{18}$$

where z indexes the origin zip code and j indexes the destination site. $distance_{zj}$ and $time_{zj}$ are the travel distance (in miles) and travel time (in minutes) by driving between the centroid of each origin zip code and each site. $cost\ per\ mile_y$ indicates the per-mile driving cost in year y. The hourly opportunity cost of time for recreation travel is specified as 40% of zip z's median hourly income, assuming a 40-hour work week and 50 weeks worked each year (2000 hours) (Cesario, 1976). Median annual income and cost per mile are all adjusted with inflation rate each year.

Results

The results of the nested logit site-choice model are shown in Table 1. First of all, in the nest of “trip”, the coefficient of travel cost is significantly negative at 1 % level, which is as expected since people are usually less willing to spend much in traveling to a far site to go fishing (i.e., the demand curves slope downward). Next, the estimate of Cyanobacteria concentration is negative and is significant at 1% level, implying that the probability of making a trip to sites in Lake Erie decreases when HABs around the sites increase.

On the “no trip” nest, results indicate that people from zip codes with higher median income, higher median age, and higher percentage of White people are more likely to choose to go on fishing trips on Lake Erie. People from zip codes that have higher percentage of people with a bachelor's degree and higher unemployment rate are more likely to choose not to go to Lake Erie.

We estimate a value of dissimilarity coefficient that is between 0 and 1 and significantly different from 1, indicating significant correlation between the random error terms in the trip nest site utilities. This result confirms that a nested logit model is better suited to explain the observed variation in site utilities than the standard conditional logit model, and it implies that when travel cost or site HABs change, the sites are closer substitutes for one another than the no-trip option.

Table 1. Nested Logit Regression Results

Nest	Variable	Coefficient
Trip	Travel cost ($)	-0.019***
		(0.000)
	Log(Cyanobacteria concentration (cell/ml))	-0.049***
		0.005
No Trip	Median income ($/100K)	-2.182***
		（0.011）
	Median age (/100)	-1.524***
		（0.035）
	% Unemployed	1.509***
		（0.044）
	% Bachelor	3.191***
		（0.015)
	% White	-1.968***
		(0.012)
Dissimilarity coefficient		0.433
Closure of a minor site (per-trip $)		23
Closure of all sites (per-trip $)		54

Notes: Standard errors in parentheses.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*
A full set of site-specific fixed effects were also included.

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