ECONOMIC DAMAGES OF WATER QUALITY WARNINGS AT GREAT LAKE BEACHES

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ABSTRACT

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This thesis estimates welfare impacts of two types of water quality warnings using a combined revealed-stated preference approach. The data was collected in a survey that randomly sampled visitors to 28 public beaches in Michigan and Ohio. The first essay uses a discrete choice experiment to measure preferences for common beach attributes including the presence of active or recent warnings for harmful algal blooms (HAB) or bacterial contamination. We find respondents are willing to drive over 200 miles to avoid a site with either of these warnings, with a negative lag effect for both hazards that remains at least 6 days after warnings are lifted.

The second essay builds on this understanding of beachgoers' preferences for attributes of beaches, by modeling site substitution behavior when beachgoers face warnings. We use a multi-site demand model that explicitly accounts for site substitution to estimate welfare impacts of site closures and HAB and bacterial warnings. A contraction map identifies the disutility of warnings by calibrating changes in site demands to match contingent behavior questions. The findings show that, at the average beach, season-long bacterial or HAB warnings cause losses of about 1.4 million dollars per year for either hazard. For 2019, the observed HAB and bacterial warnings caused about $5.8 million in welfare losses. This estimate accounts for beachgoers' lagged aversion to recently lifted warnings; omitting lagged effects would understate welfare losses by 34 percent. Together, the essays show that cost-benefit analyses that fail to account for the dynamic disamenity effects of HAB and bacterial warnings will likely understate the costs of these events, which are projected to increase in frequency and intensity under climate change.

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1.1: Introduction

The Great Lakes are one of the United States' most treasured natural and cultural resources and have occupied a substantial place in the nation's consciousness for centuries. With shores stretching over 4000 miles across eight US states and two Canadian provinces, these five inland lakes contain 21 percent of the world's fresh water (NOAA 2019). The Great Lakes are also a large driver of economic activity, and their maritime economy generates an average of 8.8 billion dollars in yearly wages across the tourism, recreation, and transportation sectors (NOAA 2019). Though the immediate economic impact of the Great Lakes on surrounding communities is widely understood and researched, it is much less clear how valuable the Great Lakes are to those who use their waters and shores for outdoor recreation. Because budgets for managing the Great Lakes are limited, understanding how beach and lake users value their experiences is useful information for policy makers when deciding how to use funds. This paper adds to the information about beach user preferences available to policymakers and beach managers by estimating how beach users value different beach attributes and levels of water quality.

In recent years, the health of the Great Lakes has come under threat due to increasing incidences of harmful algal blooms, large masses of plant matter which are driven in part by agricultural runoff. This runoff interacts with other environmental drivers to produce cyanobacteria, which in turn produce harmful algal blooms (also known as HABs). Additionally, the Lakes have faced perennial difficulties concerning high bacterial concentrations, chiefly caused by *E. coli*-contaminated runoff from urban wastewater, septic tanks, and livestock operations. Exposure to *E. coli* bacteria can cause cramps, diarrhea, vomiting, and life-threatening kidney failure (Mayo Clinic 2019), while exposure to HABs can cause liver damage and gastrointestinal illness (NIEHS 2020). To protect the public from the health effects of bacterial contamination and harmful algal blooms, the eight Great Lakes states have established state-level procedures for warning beach users about these events.

This paper aims to further examine how Great Lakes beach users value beach attributes, with a focus on user preferences toward HAB and bacterial warnings, and it is one of the few studies that uses a discrete choice experiment to elicit beach user preferences regarding harmful algal blooms. This study is also unique in the way that it approaches the question of how to frame these welfare effects. While most of the previous studies use beach closings to approximate the damage caused by HABs, closures are not the usual course of action taken by beach managers, at least in the short term. When a HAB is observed it is much more common for state agencies to issue HAB warnings than to close the affected beach. Accordingly, we estimate beach user preferences to avoid beaches with HAB and bacterial warnings in effect, as well as the effect that the amount of time since the expiration of a past warning has on these preferences.

We find that both HAB and bacterial warnings have the potential to affect beach visitation behavior for significantly longer than the warning is in place. While large HAB events have dominated the news cycle in recent years, we find that beach users are willing to drive longer distances to avoid beaches with bacterial warnings in effect, relative to similar sites with HAB warnings in effect. We also find that preferences to avoid HAB- and bacteria-affected beaches behave differently over time, with the disutility of visiting a site with a recent HAB warning dying off more quickly in comparison to a site with a recent bacterial warning.

The structure of this paper is as follows. Section 1.3 outlines random utility theory and its application to questions in environmental and resource economics, and summarizes the techniques used in this paper for modeling preferences. Section 1.4 describes our data collection process, survey pretesting and the choice experiment. Section 1.5 presents the results of the study, and Section 1.6 discusses robustness checks. Finally, Section 1.7 discusses possible policy implications of this work and explores validity and further implications of our results using auxiliary survey data. Section 1.8 concludes.

1.2: Background

Lake Erie and Lake St. Clair, a smaller lake which lies between Erie and Lake Huron to the north, are the focus of our analysis. Lake Erie is connected to Lake St. Clair by the Detroit River, and in turn the St. Clair River connects Lake St. Clair with Lake Huron. Bordered by the states of Michigan, Ohio, Pennsylvania, and New York, Lake Erie is the world's 12th largest lake by surface area (Ohio Geological Survey 2014). The Ohio Geological Survey estimates that the Ohio shoreline occupies 312 miles of Erie's 800-mile coast.

Over the past decade, Lake Erie has become a locus of severe and widely publicized HAB incidents. In the summer of 2011, Lake Erie experienced its largest HAB on record, hypothesized by researchers to be caused by increased nutrient loadings brought on by heavy rainfall as well as above-average temperatures (Michalak et al. 2013). Just three years later in August 2014, another HAB event in Lake Erie contaminated the city of Toledo's water supply, affecting over 400,000 people and resulting in the declaration of a state of emergency by then-Ohio governor John Kasich.

This marked increase in HAB events is far from a recent and isolated occurrence. Using satellite data of 71 lakes around the world, researchers at the Carnegie Institute for Science found that in 68% of these lakes, peak summertime bloom intensity has been steadily increasing since the 1980s (Ho et al. 2013). Additionally, in 2019 the United Nations Intergovernmental Panel on Climate Change reported that increasing global water temperatures, in conjunction with business-as-usual agricultural practices, have the potential to increase this upward trend (IPCC 2019). This possibility is worrisome, especially for coastal communities in areas like Ohio which depend on already HAB-prone waters for drinking water, tourism, and recreation.

Ohio and Michigan both maintain active, publicly available "BeachGuard" websites, where daily updates about beach warnings and closures are posted. Since HAB events are not very prevalent in Lake St. Clair or along the Michigan coast of Lake Erie, the Michigan BeachGuard website mostly functions as a bacterial contamination warning system. If dangerous levels of bacteria are detected off the coast of Michigan, a notification is posted to the website, a warning sign is posted on the beach in question, and in some cases the beach is closed to the public. Ohio follows a similar procedure for cases of bacterial contamination. Additionally, when toxins from harmful algal blooms are observed beyond a certain threshold, the Ohio Environmental Protection Agency declares a Recreational Public Health Warning, and a sign is posted on the affected beach warning visitors of the possible health impacts of coming in contact with HABs (Ohio EPA 2019).

To estimate Lakes Erie and St. Clair beach users' preferences to experience (or avoid) a series of regionally common beach characteristics including harmful algal bloom warnings and bacterial warnings, we use a discrete choice experiment administered to Lake Erie and Lake St. Clair beach users. In the experiment, respondents are presented with five different choice situations, in which they are asked to choose which of two beaches they would rather visit. In each choice situation, respondents can also select that they would not visit either beach. Each proposed beach alternative is described by a set of attributes, and the levels of the attributes vary between and across alternatives. By observing how respondents choose between site alternatives, we will be able to estimate marginal utility parameters, and willingness to drive (WTD) metrics, for each attribute (Haab and McConnell 2003, Freeman et al. 2014). In the case of beach attributes that may negatively impact utility, such as the presence of a HAB or bacterial warning, these WTD metrics can be thought of as respondents' willingness to drive to avoid the hazard.

If a researcher decides to use a revealed-preference approach such as a travel cost model, identifying the effects of differing levels of environmental attributes on beach use requires significant sample variation across in the levels of these attributes (Haab and McConnell 2003) and the variation needs to be independent of any unmeasured site attribute. However, due to the logistic and time constraints of primary data collection, researchers are often unable to sample over long-enough time scales for gathering sufficient variation in environmental attributes in observed trips. In the case of assessing the welfare impacts of harmful algal blooms and bacterial contamination, this problem is exacerbated since these events are largely stochastic and typically only occur a few times per season in any given body of water. Stated preference approaches are well suited to this type of research, as they allow analysts to identify and evaluate the effects of environmental scenarios that may not have been present during the study's timeframe.

Previously, researchers have used several different valuation techniques, including choice experiments, to measure how much beach users value changes in water quality and other beach attributes. Loomis and Santiago (2013) use both a choice experiment and a contingent valuation survey to estimate per-visitor, per-day values of both water clarity and the elimination of trash on Puerto Rican beaches, finding that the estimates of these values ($51 and $103, respectively) are statistically robust to the elicitation method. Beharry-Borg and Scarpa (2010) use a choice experiment to estimate Tobago beach users' willingness to pay for several different metrics of water quality, and then examine preference heterogeneity using a mixed logit model and a latent class model. Hilger and Hanemann (2006) also use a latent class model to infer consumer valuations of water quality from self-reported trip data collected from visitors to Southern California beaches. While most of these studies rely on respondent-perceived water quality metrics, Egan et al. (2009) combine visitation data collected from Iowa beachgoers with an extensive dataset detailing biological water quality measures and use a mixed logit approach to link the two.

While the use of recreation demand models to value changes in environmental quality is common in the environmental economics literature, much less of this work is focused on the Great Lakes (and freshwater beaches in general). In one of the earlier studies to focus on the value of Great Lakes beaches, Sohngen et al. (1999) use data from intercept surveys conducted at Maumee Bay State Park and Headlands Beach State Park, both Ohio beaches on the Erie coast, to value single day trips to both sites. They find average single-day trip values of $25 for Maumee and $16 for Headlands, which aggregate to $6.1 and 3.5 billion dollars in annual value, respectively. In another early study, Murray et al. (2001) estimate the value of reducing *E. coli* advisories using intercept data collected from visitors at 15 Lake Erie beaches. Importantly, their intercept survey asked beach users whether or not they take advantage of publicly-available data on current beach advisories when deciding whether or not to make a trip, and the researchers found that visitors who use this data would gain on average $24 per year from one less beach advisory. Meanwhile, beach users who only use signs posted at the beach during an advisory would gain more from the reduction of an advisory, roughly $38 per year. Song et al. (2010) use a survey of a web-based consumer panel of Michigan residents to calculate the welfare effects of beach closings at Great Lakes beaches in Michigan, including Lake Erie and Lake St. Clair. They find that closing one of Michigan's beaches would result in a loss of around $50 per person, per trip. Additionally, the researchers use the number of beach advisories and closures at a given beach during 2006 as a proxy variable for the water quality at that beach, although the number of beach advisories was not significant in their demand model and they did not control for possible correlation with unobserved beach attributes.

In one of the first studies to focus explicitly on the welfare impacts of HABs in western Lake Erie, Palm-Forster et al. (2016) build on earlier work by Chen (2013) which estimated beach visitation for Great Lakes beaches in Michigan. Palm-Forster et al. use two benefit transfer approaches, a value transfer and a function transfer, to apply Chen's earlier model to valuing HAB-induced closures of 67 Ohio beach sites on the coast of Lake Erie. They find that the typical day trip to a western Lake Erie beach is worth about $18 per trip, and total seasonal visitation is worth roughly $2 million per year. In another study focused on the welfare effects of Erie HABs, Zhang and Sohngen (2018) use choice experiment data from a survey of Ohio anglers to estimate angler willingness to pay to avoid HABs. Using several different discrete choice models including mixed logit and latent class logit to account for angler preference heterogeneity, the researchers find anglers are willing to pay $8-$11 more to avoid boating through a HAB on the way to a fishing site. Finally, Wolf et al. (2019) use survey data and a latent-class framework to simulate the welfare effects of HABs and *E. coli* events in Lake Erie on both beach users and anglers. By simulating the full closure of all western Lake Erie beaches due to poor water quality conditions, the researchers find that beachgoers and anglers would annually lose $7 million and $69 million, respectively, as a result of these closures. Additionally, they find that while beachgoers are more averse to *E. coli*, anglers are more averse to algae. This prior research has shown that water quality is a valuable good for which the public is willing to pay. Recent work focused on estimating beachgoers' willingness to pay to reduce HABs and *E. coli* warnings has advanced this understanding in the context of Great Lakes beaches, but there are still relatively few studies in this area. Additionally, much of this research uses beach closings as a proxy for warnings, yet warnings rarely result in full beach closures. Our work contributes to this literature by estimating beachgoer preferences for the presence or absence of

HAB and bacterial warnings and by specifically distinguishing between warnings and closings. This work is also the first study to consider the lagged effects of recent warnings on beachgoer preferences.

1.3: Random Utility Theory

To estimate beachgoers preferences toward beach attributes such as water clarity, HAB warnings and bacteria warnings, we use a discrete choice experiment based on random utility theory, which is widely used in transportation, environmental, and other areas of applied microeconomics. Pioneered by the early work of psychologists L.L. Thurstone (1927) and R. Duncan Luce (1959), random utility theory was formalized in an economic context by Daniel McFadden (1974). Random utility models provide a framework for modeling economic choices over discrete alternatives, such as which recreation site to visit. Assume that we observe an individual *i* making a choice between *J* distinct alternatives. The individual's decision process can be represented as follows:

$$\max_{\{H_i,\ I_j(\cdot)\}} \ U(H_i,\ \boldsymbol{z_i}, \boldsymbol{x})$$

$$s.t.\ \ Y_i = \textstyle\sum_j p_{ij} I_j(\cdot) + H_i \qquad (1)$$

$$\sum\nolimits_j I_j(\cdot) = 1\ \ ;\ \sum\nolimits_j I_j(\cdot)\boldsymbol{x_j} = \boldsymbol{x}$$

where $\boldsymbol{x_j}$ is a vector of site-specific variables for site *j*, $\boldsymbol{z_i}$ is a vector of individual characteristics that do not vary by alternative, Y_i is the individual's income, and p_{ij} is *i*'s price of alternative *j*. H_i is a Hicksian composite commodity, and $I_j(\cdot)$ is an indicator function equal to 1 if individual *i* chooses alternative *j*, and 0 otherwise.

For utility-maximizing individual *i*, the conditional indirect utility U_{ij} of choosing alternative *j* can be written as:

$$U_{ij} = V_{ij}\left(H_i,\ \boldsymbol{z_i},\ \boldsymbol{x_j}\right) + \varepsilon_{ij} = V_{ij}\left(Y_i - p_{ij},\ \boldsymbol{z_i}, \boldsymbol{x_j}\right) + \varepsilon_{ij} \qquad (2)$$

where we have substituted i's budget constraint for the Hicksian composite commodity H_i. U_{ij} is made up of the deterministic portion of the utility function V_{ij} and the random error term ε_{ij}. V_{ij} can be a function of both attributes of the individual and attributes of the alternative, and is commonly written as a linear-in-parameters function:

$$U_{ij} = \beta_0 + \boldsymbol{x}_{\boldsymbol{j}}'\boldsymbol{\beta_1} + \boldsymbol{z}_{\boldsymbol{i}}'\boldsymbol{\beta_2} + \lambda\left(Y_i - p_{ij}\right) + \varepsilon_{ij} \tag{3}$$

where λ represents the marginal utility of income.

When analyzing the estimated parameters in this indirect utility function, it is useful to compute a marginal rate of substitution (MRS) between a given attribute x_{j1} and the marginal utility of income. This provides an empirical estimate of the implicit trade-off individuals face between direct expenditures and attributes of the alternative. Taking the total differential of Equation (3) for optimizing choices and recognizing so that the attribute-expenditure tradeoff we are considering keeps utility constant for individual *i*, we have:

$$dU_{ij} = 0 = d\boldsymbol{x}_{\boldsymbol{j}}'\boldsymbol{\beta_1} + d\boldsymbol{z}_{\boldsymbol{i}}'\boldsymbol{\beta_2} + \left(\lambda dY_i - \lambda dp_{ij}\right) \tag{4}$$

Setting the differentials for all attributes besides x_{j1} and price equal to zero and rearranging, we have:

$$MRS_{x_{j1},p_{ij}} = \frac{d\lambda p_{ij}}{dx_{j1}} = \frac{\beta_{x_{j1}}}{\lambda} \tag{5}$$

In Equation (5), this MRS between attribute x_{j1} and p_{ij} represents the individual's willingness to pay (WTP) for a marginal increase in attribute $x_{j1} \in \boldsymbol{x_j}$, conditional on choosing *j*. Since the model only captures use values, if the individual does not choose *j*, marginal willingness to pay for x_{j1} is zero.

As the error term ε_{ij} is random from the perspective of the researcher, a natural way to conceptualize individual *i*'s decision-making process is in terms of probabilities. The probability that individual *i* chooses alternative *j* over any other alternative in the choice set *J* is given by:

$$P_{ij} = P\left[U_{ij} > U_{ik}\right] \forall k \in J,\ j \neq k \qquad (6)$$

If the researcher assumes that the error terms ε_{ij} are independent and identically distributed as type 1 extreme value, these choice probabilities take on the familiar conditional logit form (McFadden 1974):

$$P_{ij} = \pi_{ij} = \frac{exp\,(V_{ij})}{\sum_{k=1}^{J} exp\,(V_{ik})} \qquad (7)$$

which can be thought of as the expected demand for site *j*. In this context, individual *i*'s marginal willingness to pay for an increase in attribute $x_{j1}$is a function of the probability that *i* chooses alternative *j* and modifies the result in Equation (5) as follows:

$$MRS_{x_{j1},p_{ij}} = MWTP_{x_{j1}} = \frac{\pi_{ij}\beta_{x_{j1}}}{\lambda} \qquad (8)$$

In our empirical analysis, we generalize the MRS concept and estimate respondent willingness to drive for certain beach characteristics, although we later convert our results to willingness to pay measures, in both cases using Equation (5) as is common in choice experiments, while recognizing the importance of Equation (8) for actual choice settings.

Although the conditional logit model possesses several intuitive and desirable features for modeling discrete choices, it exhibits a statistical property known as independence of irrelevant alternatives (IIA): the probability ratio of choosing alternative *j* to alternative *k* remains unchanged when another alternative is added to the choice set, which can lead to unrealistic predictions of substitution behavior. A common way to relax IIA is to use a mixed logit model. Mixed logit models are a type of finite mixture model that assume the relevant preferences are drawn from a mixture of underlying population distributions (Greene 2018). In contrast to the conditional logit, which produces point estimates for the preference parameters $\boldsymbol{\beta}$, the mixed logit model estimates the mean and standard deviation of each parameter across the sample. Thus, while the conditional logit model inherently assumes that preferences are homogenous across the sample, the mixed logit allows for variation in individuals' preferences.

The mixed logit probability of individual *i* choosing alternative *j* can be written as follows:

$$P_{ij} = \int \frac{exp\,(V_{ij})}{\sum_{k=1}^{J} exp\,(V_{ik})}\, g(\boldsymbol{\beta}|\theta)d(\boldsymbol{\beta}) \qquad (9)$$

where $g(\boldsymbol{\beta}|\theta)$ is the mixing distribution specified by the analyst and θ represents the parameters of this distribution. $g(\boldsymbol{\beta}|\theta)$ can be specified as any distribution of preferences in the underlying population. The analyst can also allow for correlation among the individual attribute preferences. If an attribute parameter's standard deviation is estimated to be significantly different from zero, there is evidence of preference heterogeneity for that attribute in the sample.

The analyst can use the mixing distribution $g(\boldsymbol{\beta}|\theta)$ to further examine the shares of respondents with either positive or negative preferences for each attribute level, and this is the approach we take in our analysis. In addition, following Revelt and Train (2000), it is possible to further isolate where particular individuals lie in the sample distribution of preferences when the analyst possesses repeated choice data for each individual. By specifying the mixing distribution $g(\boldsymbol{\beta}|\theta)$, the analyst assumes that the true parameter vector $\boldsymbol{\beta}$ follows this distribution in the population. Suppose individual *i* is observed to choose between alternatives $j = 1, \ldots, J$ across $t = 1, \ldots, T$ repeated choice situations. Let $\boldsymbol{C_i} = \{C_{i1}, \ldots, C_{iT}\}$ denote the particular sequence of choices that person *i* makes across the *T* observed choice situations, and let $\boldsymbol{A_{ij}} = \{A_{ij1}, \ldots, A_{ijT}\}$ denote the attributes of the unique sequence of alternatives from which the individual chooses C_i.

We can then define $h(\boldsymbol{\beta}|\boldsymbol{C_i}, \boldsymbol{A_{ij}}, \theta)$ as the distribution of parameters in the segment of the population that would make the sequence of choices $\boldsymbol{C_i}$ when faced with $\boldsymbol{A_{ij}}$. The probability that individual *I* chooses $\boldsymbol{C_i}$ when faced with $\boldsymbol{A_{ij}}$ can be written in a modified mixed logit form:

$$P_{ij}(\boldsymbol{C_i}|\boldsymbol{A_{ij}}, \theta) = \int P_{ij}(\boldsymbol{C_i}|\boldsymbol{A_{ij}}, \boldsymbol{\beta}) g(\boldsymbol{\beta}|\theta) d(\boldsymbol{\beta})$$

$$= \int \prod_{t=1}^{T} \frac{exp\left(V_{iC_{it}t}\right)}{exp\left(V_{iC_{it}t}\right) + \sum_{j \neq C_{it}}^{J} exp\left(V_{ijt}\right)} g(\boldsymbol{\beta}|\theta) d(\boldsymbol{\beta}) \tag{10}$$

Using Bayes' Rule, the sub-population distribution $h(\boldsymbol{\beta}|\boldsymbol{C_i}, \boldsymbol{A_{ij}}, \theta)$ can now be computed as follows:

$$h\left(\boldsymbol{C_i}, \boldsymbol{A_{ij}}, \theta\right) = \frac{P_{ij}(\boldsymbol{C_i}|\boldsymbol{A_{ij}}, \boldsymbol{\beta}) g(\boldsymbol{\beta}|\theta)}{P_{ij}(\boldsymbol{C_i}|\boldsymbol{A_{ij}}, \theta)} \tag{11}$$

The analyst can now use this distribution to compute the conditional mean parameter vector in the sub-population of people who would make the sequence of choices $\boldsymbol{C_i}$ when faced with $\boldsymbol{A_{ij}}$:

$$E\left(\boldsymbol{C_i}, \boldsymbol{A_{ij}}\right) = \int \boldsymbol{\beta} * h\left(\boldsymbol{C_i}, \boldsymbol{A_{ij}}, \theta\right) d(\boldsymbol{\beta}) \tag{12}$$

This term does not have a closed form solution, so Revelt and Train lay out a simulation process to recover the conditional expectation. With large *T*, the conditional mean above consistently estimates the parameter vector of any individual who is observed to choose $\boldsymbol{C_i}$ when faced with $\boldsymbol{A_{ij}}$ (Train 2009). In the survey, each respondent was offered five choice situations, allowing us to examine the determinants of preference heterogeneity using the process outlined in Equations (10) through (12).

1.4: Data and Choice Experiment

The data used in this work was collected in a two-stage survey of Michigan and Ohio beach users. In the summer of 2019, we performed intercept interviews with beach users at 25 sites along the Ohio shore of Lake Erie, as well as 3 sites on the coast of Lake St. Clair and the Detroit River (Table 1.1). The 28 sites reflect coastal areas most heavily affected by harmful algae blooms and bacterial contamination. These 28 sites include all sandy beaches in this area that we could identify as open for public use during our sample period.

Table 1.1: Beach Sites Sampled in 2019

Lake or River	County, State	Site
Detroit River	Wayne, MI	Belle Isle Beach
Lake St. Clair	Macomb, MI	Lake St. Clair Metropark
		Walter & Mary Burke Park
Lake Erie	Monroe, MI	Sterling State Park
		Luna Pier Beach
	Lucas, OH	Maumee Bay State Park Erie Beach
		Maumee Bay State Park Inland Beach
	Ottawa, OH	Camp Perry Beach
		Port Clinton City Beach
		East Harbor State Park
	Erie, OH	Nickel Plate Beach
		Old Woman Creek Beach
		Sherod Park Beach
		Main Street Beach
		Showse Park Beach
	Lorain, OH	Lakeview Park Beach
		Century Park Beach
		Veteran's Memorial Park Beach
	Cuyahoga, OH	Huntington Beach
		Edgewater Park Beach
		Euclid State Park
		Sims Beach
	Lake, OH	Headlands Beach State Park
		Fairport Harbor
	Ashtabula, OH	Walnut Beach
		Geneva State Park
		Lakeshore Park Beach
		Conneaut Beach

Intercept surveys were conducted on randomly selected days between May 27th and September 1st, and each sampled day was divided into morning and afternoon shifts. After arriving at a site, interviewers walked the shoreline and counted beachgoers both in the water and on the sandy portions of the beach. Boaters in the water were excluded from these counts. Intercept interviews were then conducted with a random sample of visitors. Intercept respondents were asked about their beach recreation behavior, demographic information, and whether they would provide an e-mail address for a follow-up survey.

The intercept survey resulted in 4239 interviews for an 86% response rate (see Appendix E for a complete disposition of attempted interviews). In total, we collected 2538 (60%) usable emails of sampled beach users from the intercept survey. In May and June of 2020, these 2538 respondents were each e-mailed up to 5 invitations to the online follow-up survey. Of these invitations, 252 were undeliverable and 3 people explicitly refused to take the survey. 127 people partially completed the survey (i.e., did not answer any stated preference questions), and 1067 respondents completed the survey (47% of valid email invitations). These 1067 respondents answered an average of 4.7 out of 5 possible choice experiment questions—see Appendix E for a complete item non-response table for the stated preference questions.

In the follow-up survey, we used a discrete choice experiment to elicit stated preferences for common beach attributes, including sand quality, crowding, water quality, and the presence of harmful algal bloom and bacterial warnings. The choice experiment presented respondents with five pairs of possible sites with varying levels of beach characteristics, and asked them to choose which beach they preferred, including a “neither” option. Respondents were also asked questions about their demographic information and various other items.

As part of the survey design process, we pre-tested the follow-up survey instrument via one focus group and several cognitive interviews with Michigan and Ohio beach users. Focus groups and cognitive interviews ensure that respondents from the target population can understand the questions and tasks that they are being asked to complete and are an essential part of stated preference survey development (Kaplowitz et al. 2004, Johnston et al. 2017). In August 2019, we conducted the focus group with 14 Ohio beach users using an early version of the choice experiment. To further refine the survey instrument, we conducted 15 cognitive interviews with eligible Ohio and Michigan beach users. Interview participants were recruited from Amazon Mechanical Turk (MTurk) and the undergraduate student populations of Ohio State University and Michigan State University. The one-on-one cognitive interviews were done iteratively online via screensharing, so we were able to watch as participants completed the survey and assess how well they comprehended the questions and choice scenarios in real time. After respondents completed the survey, we further probed them on the survey instrument, focusing on the stated preference sections. The cognitive interviews resulted in several substantive changes to the choice experiment and survey.[1]

[1] For example, several respondents were confused by the inclusion of beaches with both "clear" water clarity and a harmful algal bloom warning in effect and considered this situation implausible. Our final experimental design was specified to exclude such implausible attribute combinations. Additionally, the presence of either a harmful algal bloom warning or a bacterial warning at one of the beaches in the choice experiment caused almost all respondents to choose the other beach. Thus, we expanded HAB and bacterial warning levels to include intermediate levels for the days passed since the warning was lifted.

In the choice experiment, respondents were instructed to assume that the two beaches presented in each choice set were the only beaches available to visit, and that choosing the "neither" option meant they would stay home. Each beach varied in five environmental attributes, as well as one-way distance from the respondent's home. An example of the choice experiment tables presented in the follow-up survey is shown below in Figure 1.1.

Figure 1.1: Example Choice Experiment Table

Scenario 1 of 5

Attribute	Beach A	Beach B
Sand quality	Mostly sand 	Mostly pebbles 
Presence of harmful algal bloom warning	A harmful algal bloom warning was issued for this beach a week before your trip, but was lifted 3 days before your trip.	A harmful algal bloom warning was issued for this beach a week before your trip, but was lifted 6 days before your trip.
Presence of bacterial advisory	A bacterial advisory was issued for this beach a week before your trip, but was lifted 6 days before your trip.	There is not a bacterial advisory at this beach, and there have not been any bacterial advisories here this season.
Water clarity	Clear	Somewhat murky
Crowding on the beach	Very crowded	Not crowded
Distance to beach (in miles)	**30 miles**	**70 miles**

1. Based on the beach characteristics in the table above, which beach would you choose to visit?

I would choose to visit Beach A

I would choose to visit Beach B

I would not visit any beach that day

The follow-up survey instrument began with a series of questions explaining each beach attribute and its levels, and then asked each respondent which attribute levels best described the beach where he or she was intercepted. This was done early in the survey to inform respondents about the attribute levels in a way which facilitated participation and minimized survey fatigue. Directly before the choice experiments, respondents were reminded of the attributes presented before and were offered the option to click a hyperlink that opened a summary of the attribute levels that looked similar to Table 1.2.

Sand quality was presented in three levels: mostly sand, half sand/half pebbles, and mostly pebbles, and each level was accompanied by a corresponding picture of sand taken at one of the 28 beaches included in the study. Pictures and levels of sand quality reflect the actual range of sand quality along the coasts of Lake Erie and Lake St. Clair. Water clarity was also presented in three levels: clear, somewhat murky, and very murky. To standardize these terms' meanings, we defined each water clarity level as the maximum depth at which a beach visitor can clearly see his or her submerged feet on a typical trip to the beach. Similarly, we specified the three levels of crowding (not crowded, somewhat crowded, and very crowded) in terms of how easy it is to find a spot to sit on a typical day at the given beach. During pre-test cognitive interviews, most beachgoers indicated that these descriptions made sense to them and were similar to how they usually think about these beach attributes.

The beaches presented in the choice experiment also varied in terms of harmful algal bloom and bacterial warnings (Table 1.2). The HAB and bacterial warning attribute levels indicated: there is *not* and has not been a warning at the site this season; there *is* a warning at the site, or that there is not currently a warning but there was a recent warning that expired either 1, 3 or 6 days earlier. The three intermediate levels are meant to reflect the possibility that beachgoers may care about the amount of time since the last warning was lifted, in addition to the presence of a warning.

Finally, the choice experiment included the one-way distance (in miles) from the respondent's home to the beach. The final distance levels varied individually for each respondent as 10, 50, 100, and 150 miles, plus the minimum distance from the respondent's zip code to any beach in our sample. This "minimum distance" correction ensured that none of the proposed sites in the choice experiment were implausibly close to any given respondent's residence.

Table 1.2: Choice Experiment Attribute Levels

Attribute	Levels
Sand quality	Mostly sand Half sand/ half pebbles Mostly pebbles
Water clarity	Clear Somewhat murky Very murky
Crowding	Not crowded Somewhat crowded Very crowded
Presence of bacterial warning	No warning, none this season No warning, last warning lifted {1, 3, 6} days ago Warning in effect
Presence of HAB warning	No warning, none this season No warning, last warning lifted {1, 3, 6} days ago Warning in effect
One-way distance to site	{10, 50, 100, 150} miles + minimum distance from respondent zip code to any site in the sample frame
Sand Quality Pictures	 Mostly sand  Half sand/ half pebbles  Mostly pebbles

To efficiently estimate the preference parameters in beachgoers' indirect utility functions, we used Ngene (ChoiceMetrics 2018) to generate an experimental design that minimized D-error subject to several conditions imposed on the design. Although such designs result in efficient estimates of the preference parameters used to build the design, researchers generally do not know the true distribution of preferences in the population. Therefore, when generating D-efficient designs researchers must supply prior estimates of these parameters. To ground our experimental design in empirical evidence, we conducted a pilot study to generate more informed priors and used the estimated parameter distributions from the pilot data to generate a Bayesian design for the final survey.

In addition to providing evidence-based preference priors, the pilot study allowed us to troubleshoot other early issues with the survey. We conducted the pilot in two stages. The first-stage pilot survey presented respondents with a list of the 28 beaches in our sample frame, asked respondents to indicate whether they were familiar with each beach, and which beaches (if any) they visited in 2019. If a given respondent indicated that he or she had visited any of the 28 sampled beaches at least once during 2019, the respondent was invited to complete the second-stage pilot survey containing which contained the five choice experiment questions. The second-stage pilot survey was designed to mirror the structure and information treatments of the final follow-up survey to be sent to intercept respondents. 176 respondents completed the pilot survey, supplying 880 unique choices that were used to estimate a conditional logit choice model for the Bayesian priors in our final experimental design. The final design consisted of 35 choice sets total, organized into 7 blocks of 5 choice sets each. In the follow-up survey, each respondent was randomly shown one of these 7 blocks for their 5 choice experiment tables.

1.5: Results

To examine respondents' preferences and preference heterogeneity for beach attributes, we estimate a mixed logit choice model for panel data (Train 2009). The mixed logit parameter estimates are reported below in Table 1.3.

Table 1.3: Mixed Logit Estimates[2]

Variables	(1) Mean parameter estimate	(2) Std. deviation estimate	(3) % with parameter > 0[3]	(4) Willingness to drive (WTD) at mean parameters (miles)
Distance from home (miles)	-0.0148***			
	(0.000721)			
Mostly sand	1.177***	0.680***	96	80
	(0.0892)	(0.120)		
Half sand/half pebbles	0.380***	0.0412		26
	(0.0734)	(0.145)		
Clear water	1.500***	0.662***	99	101
	(0.103)	(0.158)		
Somewhat murky water	0.707***	0.226***	99	48
	(0.0738)	(0.0836)		
Not crowded	1.011***	0.780***	90	68
	(0.0925)	(0.108)		
Somewhat crowded	0.643***	0.0873		43
	(0.0780)	(0.0829)		
Bacterial warning in effect	-3.938***	0.605		-266
	(0.267)	(0.699)		
-Lifted 1 day ago	-1.732***	0.554**	1	-117
	(0.119)	(0.236)		
-Lifted 3 days ago	-1.211***	0.180		-82
	(0.0931)	(0.150)		
-Lifted 6 days ago	-1.136***	0.00744		-77
	(0.0900)	(0.165)		
HAB warning in effect	-3.855***	1.971***	3	-260
	(0.314)	(0.475)		
-Lifted 1 day ago	-1.280***	0.200		-86
	(0.102)	(0.149)		
-Lifted 3 days ago	-0.873***	0.332**	1	-59
	(0.0870)	(0.166)		
-Lifted 6 days ago	-0.454***	0.214		-31
	(0.0780)	(0.173)		
Neither	-0.554***	1.657***	37	
	(0.127)	(0.0881)		
Respondents	1048	1048	1048	
Choice Occasions	5082	5082	5082	

[2] Robust standard errors in parentheses, *** *p*<0.01, ** *p*<0.05, * *p*<0.1. Each attribute level preference parameter is estimated relative to the following excluded base levels: "Mostly pebbles", "Very murky", "Very crowded", and "There is not a HAB/bacterial warning in effect and there have not been any warnings this season".

[3] These values are only calculated for attribute levels with significant standard deviation estimates and rely on the assumption that attribute preferences are normally distributed, which may not hold at the tails for some attributes.

Each attribute level parameter other than distance was assumed to follow a normal distribution. Mean parameter estimates for all attribute levels are significantly different from zero at the 1% level and have the expected signs, i.e., are positive on levels of attributes thought to be valued by beach users, such as sand quality, and negative on driving distance and levels of HAB and bacterial warnings. Each parameter estimate represents the marginal utility of a site attribute level relative to the relevant excluded attribute level. For example, our results indicate that, on average, respondents value a site with a half sandy/half pebbly beach more than one with mostly pebbles, all else equal. Similarly, on average respondents value a somewhat crowded beach relative to a crowded beach. The estimated distance parameter is negative and significant at the 1% level, indicating the familiar result that respondents would prefer to go to a closer beach, all else equal.

Across the site attributes, all but one adjacent pair of attribute level parameters are statistically different from one another[4] based on a Wald test, implying an intuitive and monotonic ordering of respondents' preferences. These parameter estimates provide information about the relative rankings of respondent preferences; however, it is useful to express estimates into meaningful information about travel behavior. Following Equation (5), the estimated willingness to drive (WTD) for each attribute level provide a way to discuss our parameter estimates in a more immediate and policy-relevant context. Average respondent WTD for each attribute level is reported in the final column of Table 1.3.

The most striking WTD results involve the presence of a harmful algal bloom warning and the presence of a bacterial warning. These values are -260 and -266 respectively, indicating that on average respondents would be willing to drive 260 miles to avoid a beach where a

[4] The bacterial warning parameter estimates for "3 day expired" and "6 day expired" attribute levels are not statistically different. This relationship is examined in detail later in this section.

harmful algal bloom warning is in effect, and 266 miles to avoid a beach where a bacterial warning is in effect. Considering that the state of Ohio is roughly 250 miles wide and that the median distance respondents live from the nearest beach in our sample is 15 miles[5], the magnitude of these estimates demonstrates their high importance. Additionally, these estimates indicate that to avoid either type of warning, on average respondents are willing to drive more than double the distance they would drive for a mostly sandy beach (80 miles), a beach with clear water (101 miles), or a beach that is not crowded (68 miles). It should be noted that these estimates do not account for the substitution observed in a non-hypothetical demand system. Because substitute sites exist in the real world, respondents likely would not need to drive the full distance they are willing to. Thus, the distance they incur is not the same as their willingness to drive, a difference that is akin to why willingness to pay for a good exceeds payments and yields consumer surplus.

The average respondent WTD values to avoid a site with a HAB warning in effect and a site with a bacterial warning in effect are not statistically different from one another. However, differences in preferences begin to emerge when the other three warning attribute levels are considered. Our estimates indicate that respondents are willing to drive on average 86, 59, and 31 miles to avoid a site with a HAB warning that expired 1, 3, or 6 days earlier, respectively. Similarly, respondents are willing to drive on average 117, 82, and 77 miles to avoid a site with a bacterial warning that expired 1, 3, or 6 days earlier. Estimated willingness-to-drive values at each attribute level are significantly different from one another across both types of warning.

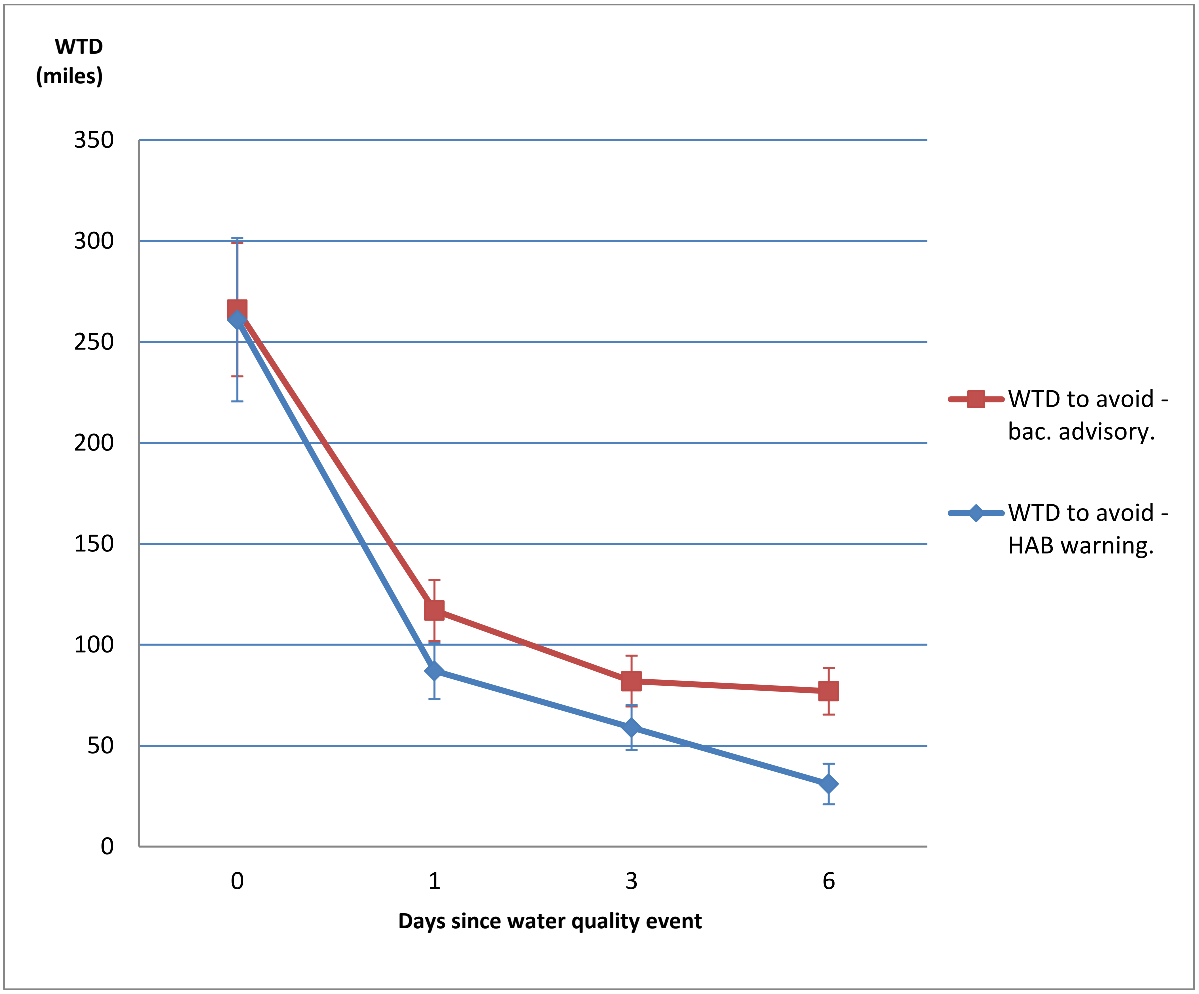
Taken together, these results imply that the disutility of each type of water quality warnings exhibit strong lag effects, and do not disappear immediately after a warning is lifted.

[5] Respondents live an average of 69 miles from their closest site in our sample. However, the median and mean travel distances for the sites where respondents were interviewed was 58 and 154 miles.

While respondents seem to be equally as averse to sites with a current HAB warning as they are to sites with a current bacterial warning, this aversion fades more quickly for HAB warnings. Respondents are willing to drive 36% farther to avoid a site with a 1-day expired bacterial warning relative to a site with a 1-day expired HAB warning and 39% farther to avoid a site with a 3-day expired bacterial warning relative to a site with a similarly recent HAB event. Additionally, respondent WTD estimates for 3-day and 6-day expired bacterial warnings are the only adjacent attribute level WTD estimates in our results that are not statistically different. In comparison, WTD to avoid a site with a recent HAB warning steadily decreases as time since the HAB warning increases. This disparity, along with the difference in magnitude between the HAB and bacterial warning WTD estimates, indicates that the preference effects of past bacterial warnings are significantly more intense, and last longer after an event, than those of HAB warnings. The behavior of respondent WTD estimates over time (at the mean parameter estimates), as well as their 95% confidence intervals, is plotted below in Figure 1.2.

Our mixed logit model allows the attribute level parameters to vary according to a multivariate normal distribution and estimates a standard deviation for each parameter. A statistically significant standard deviation estimate provides evidence of preference heterogeneity in the sample for the relevant attribute level. The parameter estimates on “Mostly sand”, “Never crowded”, and “Clear water” all exhibit heterogeneity in the sample. This makes intuitive sense, as it is likely that different beachgoers value certain beach characteristics more than others, which in turn affects their choice of sites and travel behavior.

Figure 1.2: Mean Willingness to Drive to Avoid Sites with Recent Water Quality Events and 95% Confidence Intervals around the Means[6]



The standard deviation estimates also reveal it is unlikely that any of the warning attributes are positively valued by beachgoers. Although the vast majority of respondents are estimated to have positive marginal utility for the best levels of crowding, sand quality, and water clarity,[7] the magnitude of this positive valuation significantly varies in the sample. The marginal utility of a site with the intermediate water clarity level, "Somewhat murky", relative to one with murky water, also exhibits heterogeneity in the sample. This is the only intermediate

[6] 95% confidence intervals were computed using Stata's -wtp- postestimation command (Hole 2007a)

[7] 90% for "Never crowded", 96% for "Mostly sand", 99% for "Clear water". See the second to last column of Table 1.3 for further details.

attribute level parameter across the water clarity, sand quality, and crowding attributes estimated to significantly vary across sampled beachgoers. The estimated heterogeneity in both water clarity attributes makes sense in that not all beach users enter the water during a typical beach trip, while all of our beach users interacted with the sandy portion of the beach at some time during their visit. Alternatively, regardless of whether they plan to enter the water, people are unlikely to prefer murky water at the beach; 99% of respondents are estimated to positively value somewhat murky water relative to murky water.

Preferences for sites with a 1-day lifted bacterial warning, 3-day lifted HAB warning, and current HAB warning also exhibit significant heterogeneity among sampled beachgoers. Since the mean WTD estimates for the current HAB and bacterial attribute levels are not statistically different, this heterogeneity indicates that roughly half of sampled beachgoers would be willing to drive a longer distance to avoid a site with a HAB warning in effect than they would be to avoid a site with a bacterial warning in effect. One possible reason for this is that respondents in our sample tended to have more experience with bacterial warnings relative to HABs; while 44% of respondents indicated that they have seen a bacterial warning sign on a beach, only 34% of respondents indicated having seen a HAB warning sign. Additionally, most respondents (56%) had seen news reports of people getting sick due to bacterial contamination in bodies of water. This greater level of familiarity with bacterial contamination events may contribute to respondents' relatively homogenous preferences for bacterial warning events.

The significant standard deviation estimates for several marginal utility parameters reveal that for some beach characteristics there is a distribution of preferences across individual beachgoers, but the standard deviations do not reveal how this preference heterogeneity relates to observable characteristics of beachgoers. To examine possible determinants of preference heterogeneity in the sample, we use Stata's mixlogit command (Hole 2007b) to predict each respondent's individual marginal utility parameter for each attribute level conditional on the person's observed choices using Equation (12). For each of the 15 attribute level parameters (including "Neither"), we regress the predicted individual-specific parameter on a constant and a vector of 15 demographic and attitudinal variables from the survey that may influence the distribution of beachgoer preferences. These variables include respondent age, income, race, and gender, as well as the distance from each respondent's zip code to the closest site, the number of years each respondent has regularly visited area beaches, and whether each respondent entered the water on their intercepted trip, among others. Significant results from these regressions could assist policymakers and managers understand possible market segments of beachgoers with distinct preferences.

The results of these regressions are summarized in detail in Appendix I. The available demographic and attitudinal variables do not explain much of the variation in the conditional marginal utility parameters—the 15 regressions have an average R^2 of 0.015 with an average adjusted R^2 of 0.004. Out of the 225 estimated parameters in these regressions, 8 are significant at the 5% level, and 4 are significant at the 1% level. These results are not unprecedented; several recreation studies examining heterogeneity show that attitudes explained preference heterogeneity but demographics did not (Ehrlich et al. 2017; Campbell et al. 2014) or that demographics had substantially less explanatory power that attitudes (Komossa et al. 2019). Since our current data identifies significant preference heterogeneity but is largely unable to explain the determinants of this heterogeneity, this remains fertile ground for future research.[8]

[8] Indeed, we examined several specifications of mixed logits with discrete preference distributions (also called latent class models); these latent class models often did not converge, and those that did failed to reveal substantial differences in preferences across classes with class memberships poorly explained by demographics.

1.6: Robustness Checks

To test the sensitivity of the mixed logit estimates to different model specifications, we estimate a conditional logit model and a nested logit model with trip/no-trip nests. The results are provided in Table G.1 of Appendix G. Preference parameter estimates are stable across all three models, and estimated parameter vectors are highly correlated ($\rho > .99$ for all pairwise combinations). Consequently, our WTD estimates are robust to different distributional specifications, with an average 7% difference between the mixed and conditional logit WTD estimates and an average 4% difference between the mixed and nested logit WTD estimates.

To test the sensitivity of our estimates to sample definitions, we re-estimate mixed logit models on the following subsets of the full sample: (1) respondents that completed the survey in less than 29 minutes (the 75th percentile of task duration), (2) respondents that completed the survey in more than 8 minutes (the 10th percentile of task duration), (3) respondents that live within 50 miles of their intercept beach (the 75th percentile of distances), and (4) respondents that did not exhibit intransitive preferences in their choice experiment responses. Subsets (1) and (2) were chosen because an influence due to especially fast or slow respondents may be indicative of inattention or poor comprehension, respectively. Subset (3) was chosen to test whether preferences were swayed by differences in non-local respondents. Finally, subset (4) is tested because choices of respondents with intransitive preferences may be indicative of either irrationality or inattention.

Sensitivity analysis estimates are reported in Appendix Tables G.1 through G.4. The mean preference parameter estimates are highly stable across the four robustness subsamples, and the patterns of preference heterogeneity are similar, though as expected when sample sizes shrink there are generally fewer parameters with significant distributions. In all cases the estimated mean parameter vectors are highly correlated ($\rho > .99$ for all pairwise combinations). In addition, model estimates were compared across alternative randomized question orderings that were present in the survey (Table VIId), and the results are similarly robust to ordering effects with the pooled mean parameter vector again being similar and highly correlated with the randomized orders ($\rho > .99$).

1.7: Discussion

The estimates discussed in the previous section provide useful information about how Lake Erie and Lake St. Clair beachgoers value different beach attributes, and how their preferences for certain attributes behave in comparison to others. By forming ratios of marginal utility parameter estimates, we can further examine how the average beach user implicitly trades off different levels of environmental quality, in the form of marginal rates of substitution (MRS) of driving for quality attributes. These MRS estimates have the potential to be valuable for beach managers and state financial planners, who must make decisions about how to manage public funds and want to do so in a manner that enhances societal and environmental benefits.

Consider the mixed logit estimation results. The average beachgoer has a MRS of clear water for sandy beaches of about 1.3 and MRS estimates of the absence of bacterial warnings for sandy beaches and the absence of HAB warnings for sandy beaches of about 3.3 each[9]. These clear preferences for water-related attributes suggest that the marginal dollar of state funding would likely be better spent on pollution control than local beach maintenance. However, because sand quality affects beach recreation on every trip while HAB and bacterial warnings are comparatively rare, more detailed analysis would be needed for the purposes of program evaluation and cost-benefit analysis.

While the ratios of the WTD estimates and their ordering in relation to one another are potentially useful in a policy context, one must exercise caution when interpreting the absolute magnitude of the individual WTD estimates for different beach attribute levels. As mentioned previously, many of our estimates indicate that beach users would be willing to drive large

[9] The estimated marginal rates of substitution of the absence of HAB warnings for sandy beaches and the absence of bacterial warnings for sandy beaches are not statistically different. This is consistent with our prior result that beachgoers' WTD to avoid sites with bacterial or HAB warnings in effect are not statistically different.

distances to avoid a beach with a HAB or bacterial warning in place. The largest estimates produced by our mixed logit model indicate that the average respondent would be willing to drive almost 300 miles to avoid a beach with either a bacterial or HAB warning in effect.

To further contextualize the magnitude of our results, we can compare our WTD estimates with previous WTP estimates from the water quality valuation and recreation demand literature by converting distances to dollars. After using the cost of travel to convert the results to round trip dollar values, our WTD estimates can be viewed as roughly equivalent to WTP.[10] In one of the few studies to use a choice experiment to value HABs in Lake Erie, Zhang and Sohngen (2018) find that Lake Erie anglers would be willing to pay up to $80 per trip to avoid boating through 8 miles of a HAB. Although we have no directly comparable result for beach users, Zhang and Sohngen's choice experiment included a "water clarity" attribute which used very similar levels to those in our study. They found that boaters would be willing to pay about $96 per trip for clear water relative to murky water, which is very similar to our estimate for the average beachgoer's WTP of about $101 to avoid a beach with very murky water.

While Zhang and Sohngen offer the closest point of comparison to our estimates, other stated preference valuation work conducted in marine and international settings can help to examine the validity of our results. Marsh (2012) uses a household-level choice experiment to

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[10] 1897 unique zip-site combinations were observed in our intercept data. Round-trip travel distances (in miles) and travel times (in minutes) were computed for each observed combination using Georoute (Weber and Péclat 2017). For each combination, we computed the travel cost from zip code *z* to site *j* as follows:

$$TC_{zj}=dist_{zj}*\$0.27+time_{zj}*(1/3)*(median\ income_{z}/2000)$$

Per-mile driving cost of $0.27 is computed with AAA's Your Driving Costs report (AAA 2019) using a weighted average across vehicle types and assuming 15,000 miles driven per year. Opportunity cost of time is specified using zip code z's median income, obtained from the 2018 ACS 5-year Estimates (US Census Bureau 2019) and assumes 50 weeks worked per year and 40 hours worked a week. To obtain the factor to convert WTD to WTP, we divide round-trip travel cost by travel distance and average across all observed combinations. The resulting cost is $0.47 per mile. Since a WTP measure using travel cost would typically be a round trip value, we can convert our one-way distance value by a factor of 0.5, making our one-way WTP about the same as round trip WTP.

examine how New Zealand residents value reduced probability of algal bloom warnings in two inland lakes, and finds that the average household would be willing to pay up to $138 (USD 2020) a year to reduce the probability of HAB warnings by 40%. The choice experiment was administered to a random sample of residents of New Zealand's Waikato region, and only about 35% of respondents indicated that they had visited either of the lakes in the last year. Considering that this relatively large WTP estimate was obtained from a sample which included non-users and was for a reduction in probability rather than a certain HAB as in our case, the relative value compared to our results for observed beach users make intuitive sense.

Using data from a mail survey of Finnish households, Kosenius (2010) similarly estimates yearly WTP for a series of policies designed to reduce concentrations of cyanobacteria and other types of algae. The results of the researchers' mixed logit model indicate that the average household would be willing to pay $596 per year (USD 2020) to reduce cyanobacteria and other algal biomass in Finnish coastal waters by 15- 35%. To value reduction of HABs in Quebec, L'Ecuyer-Sauvageau et al. (2018) use choice experiment responses of beach users (via intercept interviews) and residents (via door-to-door interviews) in coastal cities that had been affected by cyanobacteria blooms within the past ten years. The researchers estimate mean yearly marginal WTP for reduction of common attributes of algal blooms, such as smell, recreational impacts, and low water clarity using a mixed logit model, and aggregate these measures. They conclude that the average coastal resident in the sampled area would be willing to pay roughly $269 per year (USD 2020) to reduce the incidence of HABs. While these studies differ from ours in important methodological ways and in their focus on annual WTP for reductions of negative events, the magnitude of these WTP estimates help provide further context for our results.

Johnston et al. (2017) suggest that auxiliary evidence collected in stated preference surveys can be useful in assessing the validity of the preference elicitation mechanism. In our case, supplemental information can be used to assess how much respondents care about common beach attribute levels outside of the context of the choice experiments because our survey respondents also answered a series of contingent behavior (CB) questions The CB questions asked respondents if they would still have made the same trip to the beach where they were intercepted if faced with certain HAB and bacterial warnings at that beach on the day of their trip. The CB questions covered the same eight scenarios as covered by the HAB and bacterial warning attribute levels in the choice experiment. Table 1.4 summarizes each contingent behavior scenario and the percentage of respondents that indicated that they would have made the same trip if faced with each scenario.

Table 1.4: Contingent Behavior Response Percentages

CB Scenario	I would have gone to the same beach. (%)
Bacterial warning- day of trip	**19**
-Lifted 1 day before trip	**35**
-Lifted 3 days before trip	**53**
-Lifted 6 days before trip	**76**
HAB warning- day of trip	**19**
-Lifted 1 day before trip	**39**
-Lifted 3 days before trip	**62**
-Lifted 6 days before trip	**80**

Table 1.4 shows that as the time since the last water quality event grew, more CB question respondents indicated they would have gone to the same beach. However, about 20% of

respondents indicate that they still would not have gone to the same beach if a HAB warning had been lifted for 6 days, and 24% indicate they would not have gone to the same beach if a bacterial warning had been lifted for 6 days. For each time-since-event level, fewer respondents would have made the same trip given that the event was a bacterial warning, relative to if the event was a HAB warning. Each of these percentage estimates is statistically different from its adjacent level; however, the percentage of respondents who would have made the same trip given a bacterial warning and the percentage of respondents who would have made the same trip given a HAB warning are not statistically different from one another. Although these insights from our CB questions are consistent with and corroborate the results and patterns of the choice experiment, the CB percentages are not yet directly comparable to the parameters of the choice models.

To more directly compare the preference data gathered in the choice experiment and CB questions, we use the estimated parameters from our mixed logit model to simulate the effect of current/recent HAB and bacterial warnings on the probability of visiting a site, relative to a baseline scenario with no warnings. This requires specifying a simulation choice set and attribute levels analogous to what was shown in the choice experiments, and then using this structure to compute changes in choice probabilities corresponding to the CB scenarios. Specifically, for each follow-up respondent who answered every CB question (n = 907), we created a simulation choice set with three alternatives. The first alternative represented the site where the respondent was interviewed, and the beach attribute levels for this alternative were populated using averages of subjective environmental quality assessments collected earlier in the survey[11]. The first

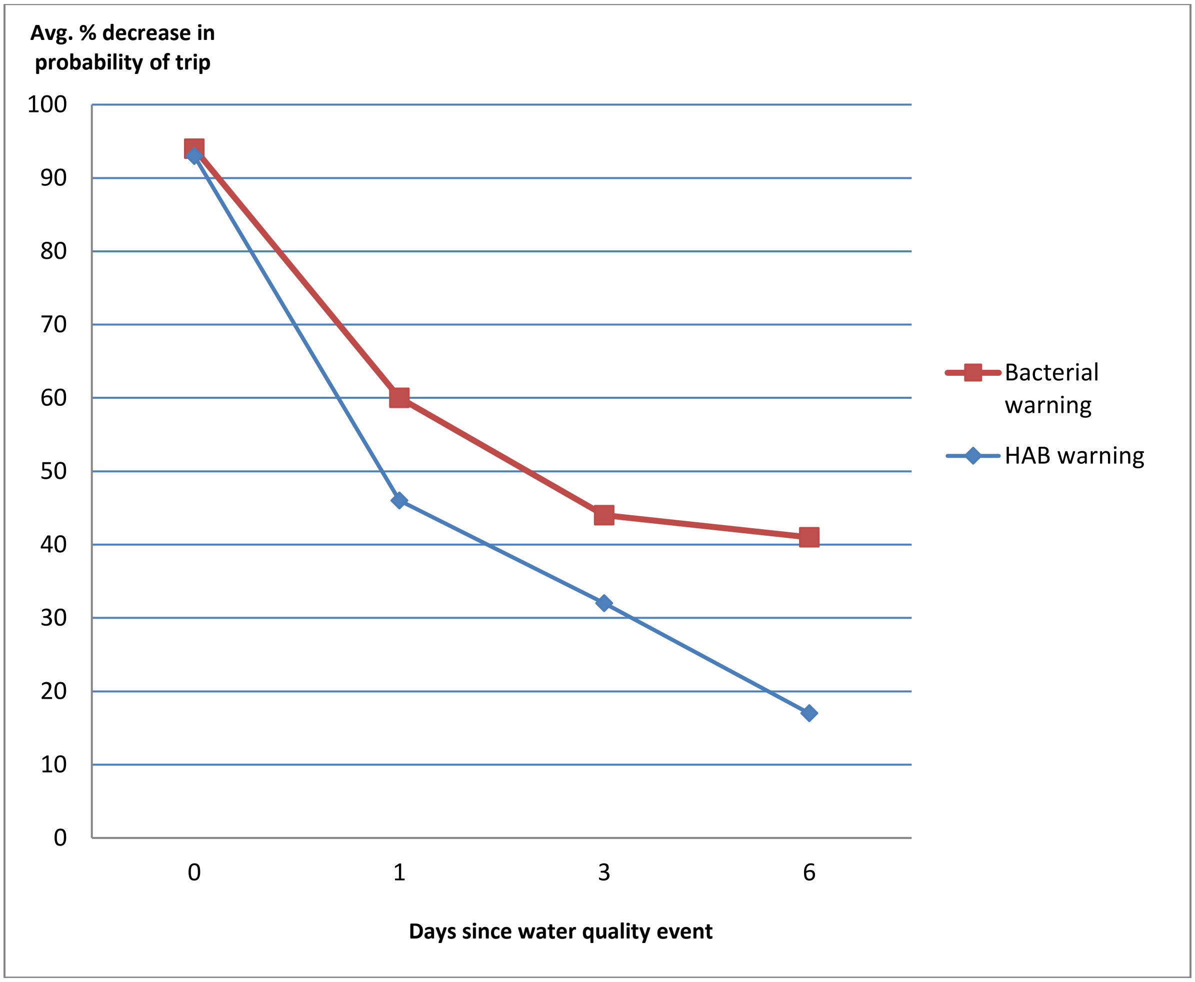
[11] In the follow-up survey, respondents were asked to report the typical levels of crowding, sand quality, and water clarity at the beach where they were interviewed. The first alternative in each respondent's simulated choice set used the average levels of sand quality, water clarity, and crowding reported by beachgoers intercepted at the same beach

alternative's distance level was the one-way distance from that respondent's zip code to their intercept site. The second alternative in each respondent's simulated choice set represented an average substitute site, and this alternative's distance level was computed as the distance from the respondent's zip code to their intercept site, plus the average distance from the respondent's intercept site to any of the other 27 sites in our sample. The third alternative in each simulation choice set was a "neither" option like the one offered in the choice experiment.

To compute baseline choice probabilities for the simulation, within each simulation choice set we set the HAB and bacterial attribute levels to zero for each respondent's "intercept beach" and "average site" alternatives and used the mixed logit's estimated preference parameters to compute the probability of each respondent visiting the beach where he or she was interviewed. In the simulation, this represented the baseline scenario with no current or recent HAB or bacterial warnings. The simulation then created 8 counterfactual beach quality scenarios to correspond to each of the 8 CB scenarios. For each counterfactual, we set the levels of the HAB and bacteria variables for each respondent's "chosen beach" to match the CB levels, and we computed the probability that each respondent would visit their intercept beach under the counterfactual. Next, we computed each respondent's percent change in probability of visiting their intercept site relative to the baseline scenario. These percent changes were then averaged across all respondents for each of the 8 scenarios. Figure 1.3 plots the average percent decrease in the probability a respondent would visit the same site for each HAB and bacterial warning scenario.

as the given respondent. The second alternative in each choice set used the average reported levels of each attribute across the whole sample.

Figure 1.3: Average Percent Decrease in the Probability of Visiting Intercepted Site, Relative to "Business-as-usual" Scenario

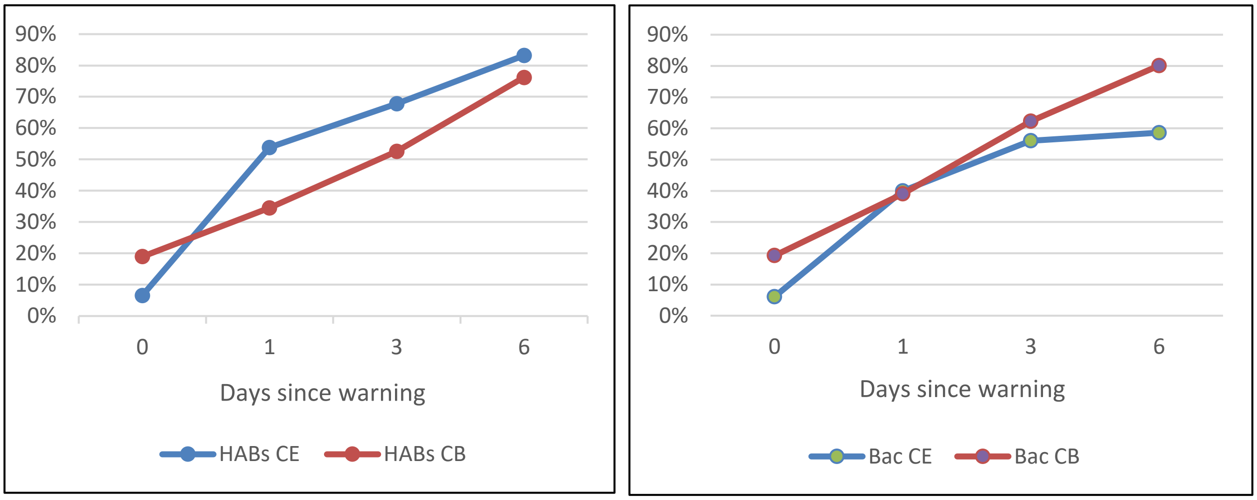


These simulated visitation probabilities are very consistent with the WTD estimates plotted previously in Figure 1.2 and offer a way to evaluate the validity of the choice experiment (CE) preference estimates. For each scenario, our CE estimates also imply that a percentage of respondents would go to the same site, and these percentages are highly correlated with the contingent behavior response percentages ($\rho = .85$) [12]. The graphs in Figure 1.4 plot the implied percentage of CE respondents who would go to the same site given a HAB or bacterial warning

[12] The similarity is particularly reassuring given the different framing of the questions – the CB question was explicitly framed about the site and time of the intercept trip whereas the CE question was about a more generic trip occasion. For a detailed table comparing the implied percentages from our choice experiment simulation with the contingent behavior response percentages, see Appendix J.

against the CB response percentages to further illustrate the high correlation between the two. Even though the mixed logit preference parameters were estimated in the context of a choice between hypothetical beaches, they are able to approximate contingent behavior scenarios concerning observed trips.

Figure 1.4: Simulated Percentages of Respondents Who Would Go to the Same Site Given a HAB or Bacterial Scenario, and Contingent Behavior Question Response Percentages



Taken together, these observations lend credence to our previous hypothesis that a temporal preference lag effect exists for HAB and bacterial warnings, and that this lag has the potential to affect travel behavior even after warnings have been lifted. The fact that such a large percentage of respondents would not make the same trip if either type of warning were in effect indicates the presence of a substantial aversion to these hazard events. Considering this auxiliary evidence, the magnitude of the estimated respondent WTD values make more sense, as such an aversion would naturally equate to a larger willingness to incur avoidance costs, all else equal.

1.8: Conclusion

This paper demonstrates that beachgoers are willing to drive farther for beaches that are less crowded, are less rocky, have higher water clarity, and do not have current or recent warnings for bacteria or HABs. In particular, the results demonstrate a significant preference lag effect concerning HAB and bacterial warnings, i.e. these events affect the visitation and welfare of beach users even after they are lifted. While respondents are willing to drive similar distances to avoid current bacterial and HAB events, the disutility of a bacterial warning lingers for much longer than a HAB warning, and the results show a remarkably similar pattern is observed in responses to the survey's contingent behavior questions. These findings have ramifications for future research and policy analyses seeking to quantify benefits of non-point source pollution control programs. If the costs of HAB and bacterial warnings are solely measured in terms of value-per lost trip during warning events, these costs will be understated.

CHAPTER 2: Economic Welfare Effects of Harmful Algal Blooms and Bacterial Contamination Warnings in the Great Lakes

2.1: Introduction

While some may consider climate change to be a distant concern, global water resources have already been impacted by climate change-induced extreme weather patterns through the increasing frequency of harmful algal bloom events. Algal blooms are water-borne masses of plant matter, which can be caused by excess agricultural nutrient runoff. Under certain environmental conditions, this runoff contributes to cyanobacteria growth in waterways, which in turn contributes to the growth of harmful algal blooms (also known as HABs). HABs can cause liver damage, gastrointestinal illness, and skin irritation for people who come into contact with them (NIEHS 2020), and they have severe ecological impacts on the bodies of water in which they appear. HAB growth routinely causes hypoxic "dead zones", depleting nutrients and oxygen that would otherwise nourish aquatic wildlife (NOAA 2020). Fish or shellfish that are not killed by this lack of oxygen and nutrients can be rendered poisonous by algal toxins, with potentially devastating effects on coastal communities who depend on aquaculture and the fishing industry for their livelihoods (CDC 2020).

High bacterial concentrations in ambient waterways, caused by runoff from untreated urban wastewater, septic tank overflow, and concentrated animal feeding operations (CAFOs), often affects the same communities which deal with HABs on a regular basis. One of the most well-known bacteria that commonly reaches unsafe levels in waterbodies is Escherichia coli (*E. coli*), exposure to which can cause cramps, diarrhea, vomiting, and in older people and children, life-threatening kidney failure (Mayo Clinic 2019). Because climate variability has been linked to more intense precipitation and more frequent flood events, increased water-borne bacterial contamination events will be a natural consequence of these changes without a large national overhaul in flood protection infrastructure and agricultural practices (Rose et al. 2001, Jung et al. 2014, Patz et al. 2008). Extreme precipitation events have been shown to be linked to past water-borne disease outbreaks (Curriero et al. 2001), underscoring the potentially large impacts of bacterial contamination on human health in the wake of rapidly changing weather patterns.

In light of the potential impacts of climate change on the frequency and intensity of HABs and bacterial contamination, policy makers and resource managers would likely benefit from information concerning the economic costs and welfare effects of these events. However, a relatively small amount of empirical research in environmental economics has sought to quantify the specific damages of HABs and bacterial contamination.

With few exceptions, the existing literature devoted to estimating the costs of HABs and bacterial contamination has used stated preference methods. Stated preference methods are useful when valuing changes in environmental quality because they allow the analyst to value quality changes that may not have occurred during the study's time frame (Carson and Hanemann 2005) or may be correlated with unobserved attributes of sites. This is especially true of HAB and bacterial events, which are random and, in the case of HAB events, usually only occur a few times per season. Despite their relative benefits, however, a drawback to stated preference studies is that they often produce willingness-to-pay estimates which may exceed what respondents would be willing to pay in real life, a concept known as hypothetical bias (List and Gallet 2001; Murphy et al. 2004; Loomis 2011).

To mitigate possible effects of hypothetical bias while taking advantage of the flexibility of stated preference methods, the use of combined RP-SP approaches in empirical valuation studies has become more common. In applications of combined RP-SP models, researchers have commonly augmented revealed preference data with contingent valuation surveys (Cameron 1992) and choice experiments (Adamowicz et al. 1994; Cheng and Lupi 2016; Whitehead and Lew 2020). Englin and Cameron (1996) was the first recreation demand study to suggest combining RP travel cost data with contingent behavior (CB) data, which asks respondents about their expected trip behavior after a price or quality change. The authors posit that CB questions may be more practical than the contingent valuation approach, as respondents may be better able to conceptualize future trips compared to the future prices offered in a contingent valuation survey. Since Englin and Cameron's original proposal, combined RP-CB methods have proven useful for answering questions in coastal resource management and environmental economics (Cameron et al. 1996; Eiswerth et al. 2000; Hanley et al. 2003).

In most of the contingent behavior literature, researchers ask respondents to report hypothetical future trips or demand behavior. An alternative approach asks respondents if they would still engage in the observed behavior given a change in price or quantity (Tanner et al. 2019; Parsons and Stefanova 2011) and seeks to ground CB scenarios in observed behavior respondents are familiar with. We take this approach and embed contingent behavior data in a revealed-preference site choice model to value Great Lakes recreation and water quality. The work is one of the few studies to value Great Lakes beaches and is one of the few to estimate the recreational costs of harmful algal blooms and bacterial contamination in freshwater more generally.

We utilize a multi-stage research strategy to examine the welfare effects of freshwater harmful algal blooms and bacterial warnings. Using responses to a rigorously designed intercept survey conducted at 28 Great Lake beaches over the course of the 2019 recreation season, we construct a multi-site, zonal dataset following the strategy developed by von Haefen et al.

(2019). Using this revealed preference data, we estimate a multi-site nested logit model of recreation demand and simulate the welfare effects of beach closures. In a follow-up survey, we elicited contingent behavior data concerning various HAB and bacterial scenarios asking beachgoers if they would have made the trip on which they were interviewed if certain HAB and bacterial events were in effect. We use the CB responses in a contraction-mapping algorithm to identify the disutilities of HAB and bacterial events, and then produce seasonal estimates of the average welfare effects of each contingent behavior scenario. We find that season-long HAB and bacterial warnings each cause welfare losses of roughly $1.4 million at the average site in our sample. We then use our estimates to simulate the welfare effects of the observed HAB and bacterial events that occurred during the 2019 recreation season, finding that these events caused roughly $5.8 million dollars in losses. We show that this estimate is about 34% larger than welfare losses computed under the assumption that beachgoers only reap disutility when warnings are in effect, illustrating the importance of accounting for the “lag” effect of beachgoer preferences in welfare estimation and policymaking. Finally, after standardized by the number of days affected by each type of warning, we show that while the majority of the 2019 season’s recreational welfare loss can be attributed to bacterial warnings, beachgoers reap more than three times more disutility from the sites that had HAB warnings than those that had bacterial warnings.

The structure of this essay is as follows. Section 2.2 provides background on water quality issues in Lakes Erie and St. Clair and reviews the available literature. Section 2.3 summarizes the on-site sampling plan used to collect intercept data, and details how the intercepted trip data is used in our revealed-preference site choice model. Section 2.4 introduces the follow-up survey, with a particular focus on the contingent behavior questions and their motivation. Section 2.5 summarizes how intercept probabilities derived from our sampling scheme are used to create our multi-site zonal dataset, and Section 2.6 outlines the theory underpinning our empirical estimation strategy. Finally, Section 2.7 and 2.8 present our results and discuss their practical significance. Section 2.9 concludes.

2.2: Background

According to the Environmental Protection Agency, HABs have been observed in all 50 US states (EPA) and are a significant and growing problem worldwide (Anderson 2012). Using satellite data of 71 lakes around the world, researchers found that in 68% of these lakes, peak summertime bloom intensity has been steadily increasing since the 1980s (Ho, Michalak, and Pahlevan 2013). Additionally, in 2019 the United Nations Intergovernmental Panel on Climate Change reported that increasing global water temperatures brought on by climate change, in conjunction with business-as-usual agricultural practices, have the potential to increase this upward trend (IPCC 2019). Because HABs can occur in freshwater, saltwater, and the brackish water between the two, the entirety of earth's water resource stock is susceptible to their effects.

Despite the relatively small amount of research concerning the welfare effects of HABs and bacterial contamination, the wide international scope of the existing literature reflects the global nature of this problem. In one of the few articles focused on measuring the welfare effects of HAB events, L'Ecuyer-Sauvageau et al. (2019) use a choice experiment on a convenience sample of Quebec residents' preferences for several nutrient-reduction policies, finding an average household willingness to pay of $269 per year (USD 2020) for eliminating the visual, recreational, odorous, and ecological consequences of HABs on local lakes. In a similar study, Kosenius (2010) uses a mail survey administered to Finnish households to estimate preferences for reduction of eutrophication in the Baltic Sea. Using a mixed logit model, the researchers find that the average household would be willing to pay $596 per year (USD 2020) for a 15-35% reduction in cyanobacteria biomass. Marsh (2012) also uses a household-level choice experiment to examine how residents of New Zealand's Waikato region value HAB reduction in two inland lakes, and finds that the average household would be willing to pay up to $138 (USD 2020) a year to reduce the probability of HAB warnings by 40%. Importantly, while L'Ecuyer-Sauvageau et al. and Kosenius frame their choice experiments by asking respondents about nutrient reduction policies and biomass levels, Marsh focuses on the reduction of HAB warnings, which is a central focus of our analysis in this paper. Finally, Taylor and Longo (2010) use a choice experiment to estimate the willingness to pay of residents of Bulgaria's Varna Bay region for HAB reduction. While the previously referenced studies find comparatively large WTP for nutrient abatement policies and HAB reduction, Taylor and Longo estimate a more modest figure, as their average respondent would be willing to pay a one-off tax of $13 (USD 2020) to fund the elimination of HABs in the Varna Bay.

In the United States, the western Lake Erie basin (consisting of Lake Erie, Lake St. Clair, and the surrounding watersheds) is one of the areas most frequently affected by HAB and bacterial events, and it is the focus of our analysis. In the summer of 2011, Lake Erie suffered from its largest HAB on record. Three years later in August of 2014, another HAB event poisoned the city of Toledo, Ohio's water supply, affecting over 400,000 people and forcing many to drive across state lines to purchase drinking water. Lake Erie's HAB problem is also not immune to the threat of climate change, and the nutrient loading reductions needed to manage Erie's eutrophication will likely be more difficult to achieve under business-as-usual agricultural practices in the coming decades (Scavia et al. 2014; IJC 2014).

In one of the earliest studies to focus on the value of Lake Erie beaches, Sohngen et al. (1999) use revealed preference intercept data to value single day trips to Maumee Bay State Park and Headlands Beach State Park, both sites on the northern coast of Ohio. They find average single-day trip values of $25 for Maumee and $16 for Headlands and aggregate these values to $6.1 and 3.5 billion dollars in annual surplus value, respectively. While Sohngen et al. do not model the effects of HAB or bacterial events on the value of these sites, Murray et al. (2001) estimate the value of reducing *E. coli* advisories using intercept data collected from visitors at 15 Lake Erie beaches. They find that beachgoers would benefit between $24 and $38 per year from one less *E. coli* advisory, and that the relative value of these welfare gains is dependent on the methods by which beachgoers learn about advisories. Zhang and Sohngen (2018) use choice experiment data to estimate Ohio anglers' willingness to pay to avoid boating through HABs, which boaters likely only must do once or twice each season, and find anglers are willing to pay $8-$11 more to avoid boating through a HAB on the way to a fishing site.

Because the majority of Lake Erie's U.S. shoreline is in Ohio, most of the existing research concerning the value of Erie beaches uses data from Ohio sites and beachgoers. However, within a larger study of all Great Lakes beaches in Michigan, Song et al. (2010) use self-reported trip data from a consumer web-based panel of Michigan residents to calculate the welfare effects of beach closings at Michigan Great Lake beaches, including Lake Erie and Lake St. Clair. They find that closing an average public beach would cause losses of roughly $50 per person per trip. The researchers suggest that these large values are likely due to the small number of substitute sites on the Michigan coasts of Erie and St. Clair (10 were considered in the study) coupled with the larger number of potential beach users in the Detroit metropolitan area. While Song et al. use the number of beach advisories and closures at a given beach during 2006 as a proxy variable for the water quality at that beach, because they do not control for unobserved beach attributes and the number of advisory days is not significant, welfare loss of an advisory is not calculated.

In one of the first studies to explicitly focus on the welfare impacts of HABs in Lake Erie, Palm-Forster et al. (2016) use a benefit transfer approach to apply an existing model of

Michigan beach recreation (Chen 2013) to valuing HAB-induced closures of 67 Ohio beach sites on the coast of Lake Erie. They find that the typical day trip to a Lake Erie beach is worth about $18 per person per trip, and they aggregate this to roughly $2 million per year in total seasonal value. In recent work, Wolf et al. (2019) use self-reported visitation data and a latent-class modeling framework to simulate the welfare effects of HAB and *E. coli* events on both beachgoers and anglers in Lake Erie. By simulating the full closure of all western Lake Erie beaches due to poor water quality conditions, the researchers find that beachgoers and anglers would annually lose $7 million and $69 million, respectively, as a result of these closures. Additionally, they find beachgoers to be comparatively more averse to *E. coli*, and anglers more averse to HABs.

While Palm-Forster et al. and Wolf et al. each reach important conclusions about the impacts of common water quality events in Lake Erie, both studies frame their discussion of worst-case welfare scenarios in terms of beach closures, and their analyses do not consider the welfare effects of HAB and *E. coli* advisories when beaches stay open. This distinction is important, as Lake Erie and Lake St. Clair beach managers typically do not close sites in response to HAB and bacterial events. This comparative infrequency of beach closure, and its implications for accurate welfare estimation, are discussed in detail later in this paper.

2.3: Onsite Counts and Intercept Survey

On randomly selected days during the 2019 summer recreation season, we conducted visitor counts and collected intercept data from Ohio and Michigan beach users at all 25 sandy public beaches along the southern and western coasts of Lake Erie, as well as 3 beaches on the coast of Lake St. Clair and the Detroit River. Interviewers approached randomly selected beachgoers at each site and asked if they would be willing to participate in a short interview about their beach visitation. At the end of each interview, respondents were given the option to participate in an online follow-up survey about their experiences with water quality at the beach. If they agreed, respondents were asked to provide an email address. The counts and intercept surveys provided revealed-preference data on beach visitation that is used to construct a recreation demand system grounded in observed travel behavior. The online follow-up survey collected contingent behavior data on trip responses to possible HAB and bacterial contamination events, which is used to identify disutilities of these events and simulate the welfare impacts within the structure of the revealed-preference site choice model.

The intercept survey was conducted randomly selected days between May 27th and September 1st, 2019. Interviews were conducted at the 25 Lake Erie sites for the entire summer season, and interviews were conducted at the 3 Lake St. Clair/Detroit River sites between June 29th and September 1st. A map of our study area is pictured in Figure 2.1, and a full list of the sites sampled in our analysis can be found in Table 2.1 below. The sites were randomly sampled within strata for weekend or weekdays and morning or afternoon shifts. After arriving at a site, interviewers walked the length of the beach and counted the number of beachgoers both in the water and on the sandy portion of the beach. Boaters in the water were excluded from these counts. After the counts, interviewers were instructed to approach every third person or group on the beach and ask if they would complete a short interview about their visit.

Figure 2.1: Study Area and Sites Used in Analysis

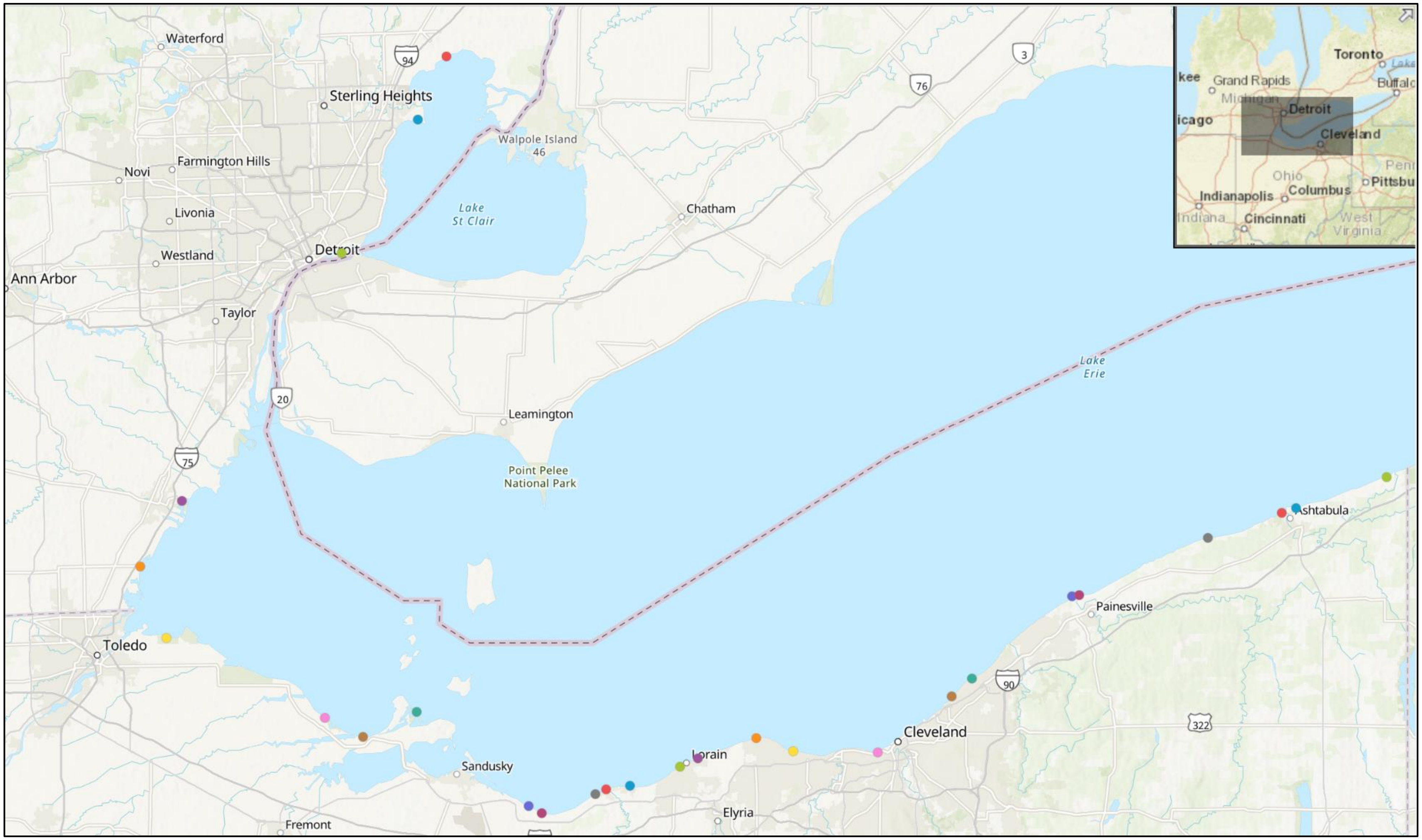


Table 2.1: Beach Sites Sampled during the 2019 Intercept Survey

Lake or River	County, State	Site
Lake St. Clair	Macomb, MI	Walter & Mary Burke Park
		Lake St. Clair Metropark
Detroit River	Wayne, MI	Belle Isle Beach
Lake Erie	Monroe, MI	Sterling State Park
		Luna Pier Beach
	Lucas, OH	Maumee Bay State Park Erie Beach
		Maumee Bay State Park Inland Beach
	Ottawa, OH	Camp Perry Beach
		Port Clinton City Beach
		East Harbor State Park
	Erie, OH	Nickel Plate Beach
		Old Woman Creek Beach
		Sherod Park Beach
		Main Street Beach
		Showse Park Beach
	Lorain, OH	Lakeview Park Beach
		Century Park Beach
		Veteran's Memorial Park Beach
	Cuyahoga, OH	Huntington Beach
		Edgewater Park Beach
		Euclid State Park
		Sims Beach
	Lake, OH	Headlands Beach State Park
		Fairport Harbor
	Ashtabula, OH	Geneva State Park
		Walnut Beach
		Lakeshore Park Beach
		Conneaut Beach

If an interviewer approached a group of beachgoers, he or she was instructed to ask to speak to the person 18 years or older with the most recent birthday, to ensure that respondent selection was random. Respondents were asked questions about their beach recreation behavior, including how many people traveled to the beach in the same vehicle with them. After asking about respondents' demographic information, interviewers asked respondents whether they would participate in a follow-up survey. If they agreed, respondents were asked to provide an email address for the follow-up survey.

The 2019 intercept survey resulted in 4239 initial observations and an 86% response rate, and of these, 4159 usable intercept observations[13] were used to create a multi-site zonal dataset, designed to model beach site choices across the 2019 recreation season. Taking advantage of the rigorous sampling plan, each observed trip could be assigned an individual weight equal to the inverse probability of being selected for an intercept interview on a given day at a given site. These weights were then aggregated to estimate seasonal visitation from zip code *z* to destination site *j*, for all observed zip-site combinations in the usable intercept data. These estimated trips serve as the dependent variables in our repeated random utility model of site choice, which treats each origin zip code as a representative agent. The creation of the weights and zonal dataset is described in further detail later in this essay.

[13] Excluded interviews included 69 that refused to provide a zip code or provided foreign or nonexistent zip codes; 4 zip codes only accessible by boat; 4 zip codes for which the round-trip driving cost could otherwise not be obtained, and 3 zip codes over 2500 miles from the site where they were intercepted.

2.4: Follow-Up Survey and Contingent Behavior Data

An online follow-up survey was used to gather the contingent behavior data. The follow-up survey began by asking respondents questions about their perceptions of several beach characteristics at the site where they were intercepted. Respondents were then shown information concerning the causes of HAB and bacterial warnings, as well as the possible effects of each type of event on human health and the environment. After each information page, respondents were asked questions about their personal experiences with HAB and bacterial warnings to encourage them to interact with the survey instrument. Respondents were then shown the contingent behavior questions. The survey development and questionnaire testing process followed recommendations for revealed and stated preference studies (Lupi et al. 2020; Johnston et al. 2017) and included a focus group with 14 participants, 15 individual cognitive interviews conducted in March and April of 2020, and a 176-respondent pilot survey conducted via Amazon MTurk in May 2020.

In May and June 2020, respondents who provided email addresses during the intercept survey were invited to participate in the follow-up survey. Out of the 4159 intercept participants who provided usable trip data in 2019, 2538 provided an email address. After the initial invitation email, non-respondents were sent up to 5 reminder messages over the course of a month. After the first reminder email, non-respondents were offered a $20 completion incentive. Of the 2538 contacted via email, 1067 respondents[14] (46% of deliverable emails) completed the survey, and these 1067 respondents answered an average of 8 contingent behavior questions. An item non-response table which further summarizes responses to the survey's stated preference

[14] 251 email addresses were undeliverable; 3 respondents refused; 3 opened the survey but did not click past the first page, 1194 clicked through the consent form, and 127 partially completed the survey (did not answer any stated preference questions).

questions is available in Appendix E. The nine contingent behavior scenarios used in the follow-up survey are listed below in Table 2.2.

Table 2.2: Contingent Behavior Scenarios

Type of water quality event	Contingent Behavior Scenario
Harmful algal bloom	A harmful algal bloom warning is in effect at the beach where you were interviewed.
	A harmful algal bloom warning was issued at the beach where you were interviewed 7 days before your trip, and was lifted **1 day** before your trip.
	A harmful algal bloom warning was issued at the beach where you were interviewed 7 days before your trip, and was lifted **3 days** before your trip.
	A harmful algal bloom warning was issued at the beach where you were interviewed 7 days before your trip, and was lifted **6 days** before your trip.
	A harmful algal bloom warning was issued for the **next beach along the shore** on the day you were interviewed, but no warning was issued for the beach you visited.
Bacterial contamination	A bacterial warning is in effect at the beach where you were interviewed.
	A bacterial warning was issued at the beach where you were interviewed 7 days before your trip, and was lifted **1 day** before your trip.
	A bacterial warning was issued at the beach where you were interviewed 7 days before your trip, and was lifted **3 days** before your trip.
	A bacterial warning was issued at the beach where you were interviewed 7 days before your trip, and was lifted **6 days** before your trip.

For each contingent behavior question, respondents were asked if, given the scenario described, they still would have made the same beach trip they made on the day they were interviewed. Each question had three possible answers: respondents could either indicate they would have gone to the same beach, gone to a different beach, or stayed home. The contingent behavior questions were written to reflect the hypothesis that the average beachgoer is less likely to visit a beach if he or she knows a HAB or bacterial warning is in effect at that beach. As part of our larger goal of identifying the welfare impacts of these water quality events, the questions about recently lifted warnings were used to examine whether these events have a lag effect on visitation.

2.5: Zonal Dataset

Our revealed preference site-choice model is specified as a repeated random utility model (Morey et al. 1993) to capture both site choices and seasonal participation. Traditionally, repeated RUMs estimated using individual-level data require detailed data on the number of trips taken by each person to each relevant site in order to model both the intensive and extensive margins of recreation behavior. Our model treats each origin zip code as a representative agent (English 2008) and uses site-selection and intercept probabilities derived from our original sampling design to estimate seasonal trips for each origin zip-destination site combination observed in the intercept data. Using zip code population data, we can then estimate the number of no-trip choice occasions in each zip code across the 2019 recreational season. Developed for intercept data by von Haefen et al. (2019), this approach allows us to use the survey design weights to estimate demand in a two-level nested logit framework which includes a non-participation alternative in each choice set.

Each beach user who completed a full interview at an intercept site reported his or her home zip code, and so we were able to compile a list of the unique zip-site combinations observed in the intercept data. Using the intercept data, we derive the trip estimates from each origin zone to each intercept site using inverse selection probabilities (Leggett 2017, Tourangeau et al. 2017). With the estimated number of trips from each origin zip code to each site for every unique zip-site combination, we form our zonal dataset. Let $j = 0, \ldots, J$ represent the sites in our dataset, with $j=0$ representing the no-trip option in each representative agent's choice set. The total number of possible destination sites in each choice set is $J = 28$, and the total number of alternatives in each choice set is $J+1 = 29$.

To form the inverse selection probabilities, each sampled trip is assigned to one of ten mutually exclusive strata, based on the day of the week and month when the trip was intercepted, as well as on which interviewer team (Michigan State or Ohio State) conducted the interview. The list of strata used in our trip estimation is available in Appendix K. The selection probabilities also use the trip counts conducted during each site visit. Since multiple interviewers were usually present at a site on any given day, daily beachgoer counts for each site were obtained by averaging the individual counts. Additionally, trip durations are derived from the intercept survey questions about respondents' arrival and planned departure times. Finally, because each interviewed beachgoer was asked if recreation was the primary purpose for their visit, we are able to construct $P_{rec,h}$, the probability that any given beachgoer in stratum h was engaging in recreation. These quantities are the main components used to construct our zonal trip estimates.

Following Leggett (2017) and Tourangeau et al. (2017), we first create a weight w_{hijk} for each beachgoer *k* intercepted on date *i* at site *j* in stratum *h,* as follows:

$$w_{hijk} = \frac{N_h}{n_{jh}} \frac{M_i}{\tilde{d}} \frac{\overline{c_{hij}}}{K_{hij}} P_{rec,h} \tag{1}$$

$$\tilde{d} = \left(\frac{\sum_{i=1}^{I_h} (1/d_i)}{K} \right)^{-1} \tag{2}$$

Each individual weight is equal to the inverse of the probability that beachgoer *k* was sampled. $\overline{c_{hij}}$ is the average instantaneous count of beachgoers at site *j* on day *i*, and K_{hij} is the number of beachgoers interviewed at site *j* on day *i*. M_i is the length of time, in minutes, during which instantaneous counts could have taken place on day *i*. N_h is the total number of days in stratum *h*[15], and n_{jh} is the total number of days in stratum *h* that sampled site *j*. $\tilde{d}$ is the harmonic mean of the average trip duration across the sample, which is used instead of the arithmetic mean to account for the fact that visitors who stay at a site longer have a larger probability of being intercepted[16]. The harmonic mean (Equation 2) is calculated as the inverse of the mean of the inverse trip durations, and K denotes the number of intercepted trips.

Once w_{hijk} is obtained for every intercepted beachgoer, we sum these weights over the K_h beachgoers in a given stratum *h* to recover an estimate of the total visitation in each stratum:

$$\widehat{T_h} = \sum_{k=1}^{K_h} w_{hijk} \tag{3}$$

For each origin zip-destination site combination, $\widehat{T_{zJ}}$ are the trips taken to *j* from *z* for each zip-code representative agent in our zonal dataset. We use the stratum-specific visitation estimates $\widehat{T_h}$ to construct $\widehat{T_{zJ}}$, and this process is explained in detail in Appendix K.

Additionally, we define the total estimated trips to each site ($\widehat{T_J}$) and from each origin zip code ($\widehat{T_z}$) by summing $\widehat{T_{zJ}}$ over the *Z* total origin zips and *J* sites in the choice set:

$$\widehat{T_J} = \sum_{z=1}^{Z} \widehat{T_{zJ}} \tag{4}$$

$$\widehat{T_z} = \sum_{j=1}^{J} \widehat{T_{zJ}} \tag{5}$$

Following von Haefen et al. (2019) and Tanner et al. (2019), we construct $\widehat{T_{z0}}$, the number of times in zip *z* the no-trip option was chosen during the season, using $\widehat{T_z}$ and the total population of *z*:

$$\widehat{T_{z0}} = A * pop_z - \widehat{T_z} \tag{6}$$

[15] The total number of days in each stratum varies, as the sample was stratified by month and weekend/weekday combinations (i.e., "August weekend" or "June weekday".)
[16] For detailed discussions of the use of the harmonic mean to estimate trips in the context of recreation demand modeling, see Leggett (2017), Deacon and Kolstad (2000), and Tourangeau and Ruser (1999).

$$A = \max_{z \in Z} \left\{ 1.1 * \frac{\widehat{T_z}}{pop_z} \right\} \tag{7}$$

where *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.

To prepare the zonal dataset for estimation, we use Stata's Georoute package (Weber and Peclat 2017) to compute the round-trip travel time (in minutes) and distance (in miles) between the centroid of each origin zip code and each site in our sample. Using the 2019 AAA Your Driving Costs report (AAA 2019), we construct the travel cost for each zip-site combination in each individual choice set. The travel cost accounts for per-mile driving costs as well as the opportunity cost of time[17], and is specified as follows:

$$TC_{zj} = dist_{zj} * (\$0.27\ per\ mile) + time_{zj} * \frac{1}{3} \left(\frac{median\ income_z}{2000} \right) \tag{8}$$

where *z* indexes the origin zip and *j* indexes the destination site. Median annual income for each zip code is obtained from the American Community Survey's 2018 five-year estimates (US Census Bureau 2019). Our per-mile driving cost of $0.27 is computed using a weighted average of costs across vehicle types from the AAA Your Driving Costs report for 15,000 miles driven each year. The driving cost is made up of maintenance costs as well as marginal depreciation costs (Lupi et al. 2020). The hourly value of time for recreation travel is specified as one-third of zip *z*'s median hourly income, assuming a 40-hour work week and 50 weeks worked each year.

The zonal dataset was constructed using the intercept interviews and is described in detail in Table 2.3 below. The dataset was made up of 4159 individual beachgoers from 999 origin zip codes. Within this data, we observed 1896 unique origin zip-destination site combinations. At the individual level, 95 percent of respondents indicated that recreation was the primary purpose of

[17] For a survey of the recreation demand literature concerning how to construct travel costs, as well as a discussion of the challenges inherent in measuring the value of travel time, see Lupi, Phaneuf, and von Haefen (2020).

their visit. Respondents spent a harmonic average of 104 minutes at sites. The 999 origin zip codes had an average median income of $61,938, and an average median age of about 41 years old. The average origin zip code was predominantly white (82%) and was 5% Hispanic. At the trip-site level, the average estimated number of trips from origin zip z to destination site j ($\widehat{T_{zj}}$) was 777. Estimated total trips from zip code z ($\widehat{T_z}$) range from 28 to 38,465 with an average of 1475 and estimated total trips to any site j (T_j) range from 1717 to 262,944, with an average of 52,638 trips.

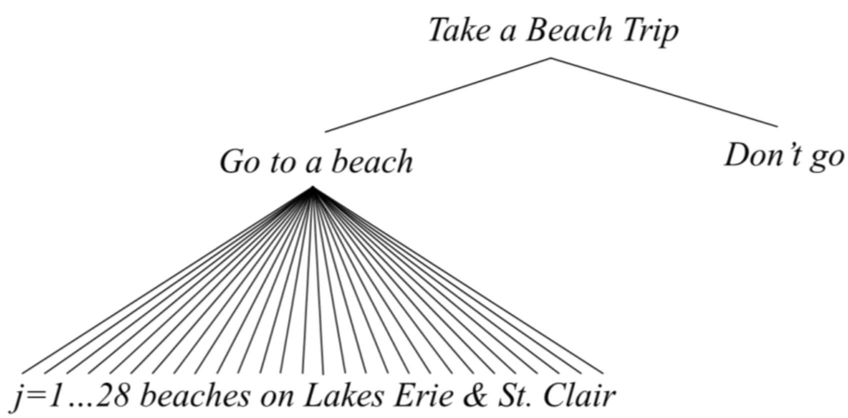
Table 2.3: Zonal Dataset Descriptive Statistics

		Arithmetic Mean	Harmonic Mean	Median	Min	Max	N
Individual	Recreation primary purpose of beach	0.95		1	0	1	4159
	Time spent at site (minutes)	175.9	104.4	165	5	870	4159
Trip Variables	Visits from origin zip ***z*** to destination	777		356	28	31,301	1896
	Visits from origin zip ***z*** ($\widehat{T}_z$)	1475		495	28	38,465	999
	Visits to destination site ***j*** ($\widehat{T}_j$)	52,638		35,478	1757	262,94	28
Origin Zip	Median household income ($)	61,938		58,495	11,049	201,23	999
	College degree (%)	29.5		25	3	85	999
	Median age (years)	40.8		41	19	66	999
	Hispanic (%)	5.1		3	0	69	999
	White (%)	82.3		90	2	100	999
	Unemployment rate (%)	5.9		5	0	30	999
Trip Statistics	Round trip distance to any site (miles)	571		336.2	1.2	5126.4	27,972
	Round trip distance to visited site	308.5		115.5	1.2	4975.9	1896
	Round trip travel cost to any site ($)	259.9		148.6	1.2	3313	27,972
	Round trip travel cost to visited site ($)	143		52.7	1.2	3212.4	1896

2.6: Site Choice Model and Calibration to Stated Preference Data

Our site choice model is rooted in random utility maximization theory and uses revealed preference data to model the recreation decision process in a two-level nested logit framework. In each choice occasion, individuals decide whether to make a trip and conditional on a trip, they decide which of the 28 sites ($j = 1, \dots, 28$) to visit. In keeping with the traditional assumptions of RUM theory, we assume that an agent chooses alternative j if it yields the most utility out of all the available alternatives in the choice set. Figure 2.2 below illustrates the nests within our model, where the site nest alternatives may have errors that are more correlated with one another than with the "no-trip" alterative.

Figure 2.2: Nesting Structure for Repeated Nested Logit Model of Great Lakes Beaches



The conditional indirect utility an individual from zip code z receives from choosing the no-trip option ($j = 0$) is composed of an observable representative utility component and a random error term, unobservable to the researcher. Representative utility for the no-trip option is specified as a function of zip-level demographic variables obtained from the 2018 American Community Survey five-year estimates:

$$U_{z0} = V_{z0} + \varepsilon_{z0} = \beta_{inc} med.income_z + \beta_{age} med.age_z + \beta_{coll} \%coll.grad_z +$$

$$\beta_{emp} \%employed_z + \beta_{white} \%white_z + \beta_{hisp} \%hispanic_z + \varepsilon_{z0} \quad (9)$$

The conditional indirect utility an individual from zip code *z* receives from choosing to visit site *j*≠0 is also composed of representative utility and a random error term, where the representative utility term is specified as a function of the travel cost from zip code *z* to site *j*≠0:

$$U_{zj} = V_{zj} + \varepsilon_{zj} = \beta_{TC} TC_{zj} + \alpha_j + \varepsilon_{zj} \quad (10)$$

Here, 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. Because random utility models are defined in terms of utility differences, of the J+1 alternatives in the repeated RUM, only *J* =28 constants are identified for estimation (one for each site in the choice set).

The probability that a person from zip *z* chooses site *j* can be expressed as the product of $P_{z,trip}$, the probability that a person from *z* takes a trip, and $P_{zj|trip}$, the conditional probability of choosing site *j*:

$$P_{zj} = P_{z,trip} P_{zj|trip} \quad (11)$$

Because we model the site-choice process in a nested-logit framework, we assume the random error terms ε_{zj} follow a generalized extreme value (GEV) distribution, and write the components of P_{zj} as follows:

$$P_{z,trip} = \frac{exp\,[\tau * \ln(\sum_{k=1}^{28} exp\,(\frac{1}{\tau} V_{zk}))]}{exp(V_{z0}) + exp\,[\tau * \ln(\sum_{k=1}^{28} exp\,(\frac{1}{\tau} V_{zk}))]}$$

$$= \frac{[\sum_{k=1}^{28} exp\,(\frac{1}{\tau} V_{zk})]^{\tau}}{exp(V_{z0}) + [\sum_{k=1}^{28} exp\,(\frac{1}{\tau} V_{zk})]^{\tau}}$$

$$P_{zj|trip} = \frac{exp\,(\frac{1}{\tau}V_{zj})}{\sum_{k=1}^{28} exp\,(\frac{1}{\tau}V_{zk})} \quad (12)$$

Train (2009) shows how these probabilities are obtained by decomposing the structural P_{zj} term derived from the multivariate GEV distribution. The dissimilarity coefficient τ reflects the degree to which the random error terms in each site utility are correlated, with a lower value of τ indicating more correlation. The term $\ln(\sum_{k=1}^{28} exp\,(\frac{1}{\tau}V_{zk}))$, which appears in the numerator of $P_{z,trip}$, is often called the log-sum or inclusive value term. The inclusive value represents the expected utility that a representative agent reaps from the ability to choose between the site alternatives in the *trip* nest and is a central quantity in our empirical welfare estimation later in this essay. As the inclusive value increases, the probability that an agent chooses to make a trip increases as well, an intuitive result that connects the upper and lower nests of the choice structure.

In our empirical estimation, we first examine the welfare effects of site closure. To do so, we use the concept of compensating variation (CV). Following a change in the price or quality of a good, the compensating variation is the amount of money that leaves an economic agent as well off, in terms of utility, as they were before the change. Specifically, consider a set of recreation sites J^0 which are substitutes, and with level of environmental quality Q^0. Now suppose a policy change or natural event shifts the quality level and number of viable sites from (Q^0,J^0) to (Q^1,J^1). Defining S_z as a vector of demographic variables for representative agent *z*, the compensating variation per choice occasion for agent *z* can be implicitly defined as follows:

$$\max_{j\in J^1}[V\big(Y - TC_{zj}, Q^1, S_z\big) + \varepsilon_{zj}\big] = \max_{j\in J^0}[V(Y - TC_{zj} - CV, Q^0, S_z)] \quad (13)$$

Specifying the linear functional form of our site-choice model and rearranging, we can isolate the CV term. Because our model accounts for site-specific environmental quality variation using alternative-specific constants, we represent the change to Q^1 by adding a term Δ_{Q1} to the relevant constant:

$$\left(Y - TC^1_{zj,max}\right)\beta_{TC} + S'_z\beta_s + \left(\alpha^1_{j,max} + \Delta_{Q1}\right) + \varepsilon^1_{zj,max}$$
$$= \left(Y - TC^0_{zj,max} - CV\right)\beta_{TC} + S'_z\beta_s + \alpha^0_{j,max} + \varepsilon^0_{zj,max} \quad (14)$$

$$\leftrightarrow$$

$$CV = \frac{1}{-\beta_{TC}}\begin{bmatrix}\left(-TC^1_{zj,max}\beta_{TC} + S'_z\beta_s + \left(\alpha^1_{j,max} + \Delta_{Q1}\right) + \varepsilon^1_{zj,max}\right) \\ -\left(-TC^0_{zj,max}\beta_{TC} + S'_z\beta_s + \alpha^0_{j,max} + \varepsilon^0_{zj,max}\right)\end{bmatrix} \quad (15)$$

To aggregate this welfare measure to a full recreation season, we multiply per-choice occasion CV by each agent's choice occasions,[18] and sum over all agents Z:

$$CV_{CLOSURE} = \sum_{z=1}^{Z} CO_z \frac{1}{-\beta_{TC}}\begin{bmatrix}-\left(TC^1_{zj,max}\beta_{TC} + S'_z\beta_s + \left(\alpha^1_{j,max} + \Delta_{Q1}\right) + \varepsilon^1_{zj,max}\right) \\ -\left(-TC^0_{zj,max}\beta_{TC} + S'_z\beta_s + \alpha^0_{j,max} + \varepsilon^0_{zj,max}\right)\end{bmatrix} \quad (16)$$

For the analyst, the best sites and the error terms are unknown, so expectations are taken. Given our model is a nested logit, the expected compensating variation for site closures or quality changes can be written as a function of the monetized difference between two inclusive value terms, which represent the maximum expected utilities that can be achieved under baseline and post-change conditions. For our purposes, let $\Delta_{Q1,J}$ denote an adjustment to site *j*'s ASC which represents a quality change, or in the case of a closure, a larger change that drives predicted trips to *j* to zero. Here, $\mathrm{I}_j[\Delta_{Q1,J}]$ is an indicator function which equals $\Delta_{Q1,J}$ if site *j* is affected, and zero otherwise:

$$CV = \sum_{z=1}^{Z} CO_z \frac{1}{-\beta_{TC}}\begin{bmatrix}\ln\left(exp(V_{z0}) + \left[\sum_{k=1}^{27} exp\left(\frac{1}{\tau}(V_{zk} + \mathrm{I}_j[\Delta_{Q1,J}])\right)\right]^{\tau}\right) \\ -\ln\left(exp(V_{z0}) + \left[\sum_{k=1}^{27} exp\left(\frac{1}{\tau}V_{zk}\right)\right]^{\tau}\right)\end{bmatrix} \quad (17)$$

[18] For events which vary over the season, we can sum the measure over the relevant choice occasions rather than simply multiplying by choice occasions.

The average seasonal welfare effect of a given scenario *s* at site(s) *j*≠0 is evaluated using Equation (17) above (English et al. 2018).

Because harmful algal bloom and bacterial warnings do not usually result in beach closings, we are interested in the welfare effects of these events when sites stay open. To estimate the welfare effect of beach closures, we use data from respondents' answers to the 9 contingent behavior questions in the online follow-up survey. Respondents were asked whether, given each of the algae/bacterial scenarios in Table 2.2, they would have gone to another site on the day they were interviewed. Because each site's ASC captures unobserved environmental quality attributes that affect site utility, we adjust each site's constant to identify the disutility of different warning scenarios. Following Tanner et al. (2019) and English et al. (2018), we adjust the alternative-specific constant for each site *j*≠0 and each scenario *s*:

$$\alpha_j^s = \alpha_j + \Delta_j^s \tag{18}$$

For each site in the choice set, we can obtain σ_j^s, the percentage of follow-up respondents who indicated they would have gone to the same site under scenario *s*. The above adjustments to the alternative specific constants are made to replicate the pattern of demand predicted by the contingent behavior responses; in other words, the adjustments solve for the value of $Trips_j^s$ that satisfies the following equation:

$$Trips_j^s = \sigma_j^s Trips_j \tag{19}$$

For each site-scenario combination, we recalibrate the initial ASCs and solve for Δ_j^s using an iterative contraction mapping algorithm. This method has been most notably used to calibrate automobile market share data for demand forecasting (Berry, Levinsohn, and Pakes 1995)[19], and has been applied to recreation demand by Murdock (2006), English et al. (2018) and Tanner et

[19] For a discussion of this technique as applied to empirical industrial organization, see pp. 32-33 of Train (2009).

al. (2019)[20]. The contraction mapping estimates values of Δ_j^s, which are then used to repeatedly compute guesses of $\widehat{Trips}_j^s$ until it is as close as possible to $Trips_j^s$. The algorithm begins by guessing $\Delta_{j,0}^s$, adjusting the ASC, and estimating $\widehat{Trips}_{j0}^s$. Then for each successive iteration *k*, the algorithm calculates $\Delta_{j,k+1}^s$ as follows:

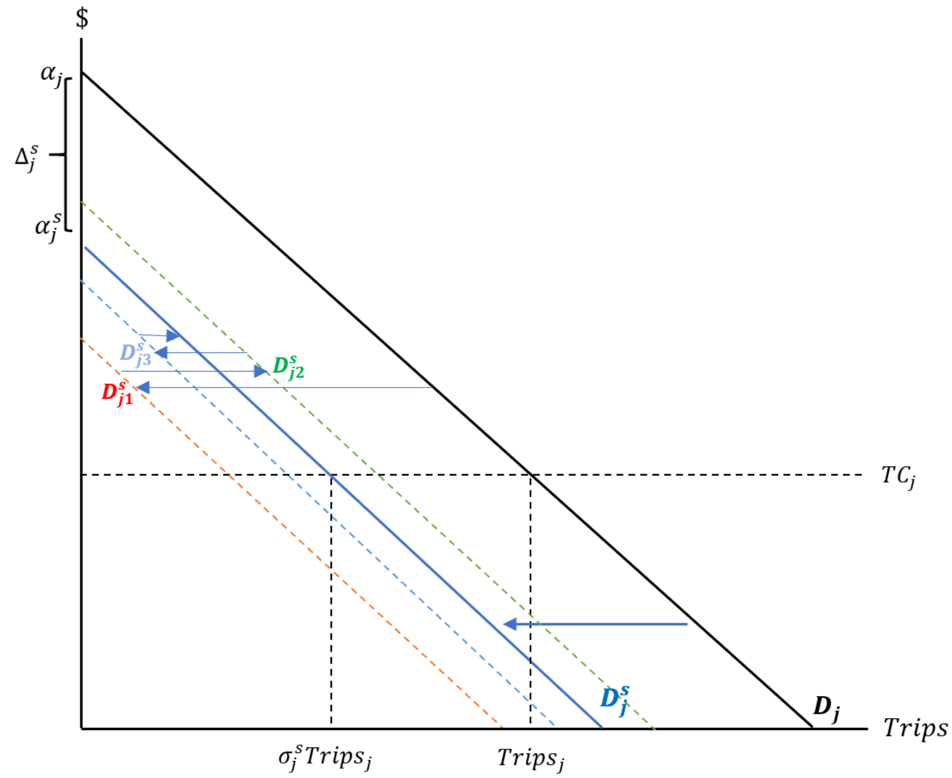
$$\Delta_{j,k+1}^s = \Delta_{j,k}^s + [ln\left(Trips_j^s\right) - ln\,(\,\widehat{Trips}_{jk}^s)] \tag{20}$$

Once the constants have been recalibrated, we can use them to estimate the welfare effects of the 9 different water quality scenarios. For each scenario *s* we compute $\overline{\Delta^s}$, the weighted average of the ASC adjustment terms Δ_j^s across the *J* = 28 sites.

Figure 2.3 below illustrates the contraction mapping graphically in price-quantity space, and it shows how the algorithm iteratively guesses values of Δ_j^s until $Trips_j^s$ is reached. The movement from D_j to D_j^s reflects the downward shift in recreation demand induced by warning scenario *s* at site *j*. In the illustration, D_{j1}^s, the algorithm's first guess, understates the targeted demand, D_{j2}^s overstates the target, and D_{j3}^s once again understates the target but less dramatically than D_{j1}^s. This pattern continues until D_j^s is reached. Δ_j^s is the disutility adjustment that moves the original ASC α_j to the calibrated term, α_j^s.

[20] Anciaes, Metcalfe, and Sen (2020) also use the same contraction mapping algorithm to calibrate choice experiment responses to an RP model to estimate the preferences of UK anglers for site attributes.

Figure 2.3: Contraction Mapping Algorithm



Naturally, high-use beach sites will likely incur higher recreational welfare losses from HAB and bacterial scenarios, relative to less popular sites. To standardize our welfare estimates and compare the impacts of different water quality scenarios at both high-use and low-use sites, we divide the CV term in Equation (17) by the predicted change in trips under scenario ***s*** to recover an estimate of the value per lost trip associated with *s*:

$$CV_j^s \ per\ lost\ trip$$
$$= \frac{\sum_{z=1}^{Z} CO_z \frac{1}{\beta_{TC}} \left[\ln\left(exp(V_{z0}) + \left[\sum_{k=1}^{28} exp\left(\frac{1}{\tau} (V_{zk} + \mathrm{I}_j [\,\overline{\Delta^s}]) \right) \right]^{\tau} \right) - \ln\left(exp(V_{z0}) + \left[\sum_{k=1}^{28} exp\left(\frac{1}{\tau} V_{zk} \right) \right]^{\tau} \right) \right]}{\sum_{z=1}^{Z} CO_z P_{zj} - \sum_{z=1}^{Z} CO_z P_{zj}^s} \quad (21)$$

where $CO_z = A * pop_z$ is equal to the specified number of choice occasions for zip code *z*.

2.7: Results

Table 2.4 lists the percentage breakdown of responses to the contingent behavior questions, along with the standard errors of these percentages. Roughly 81 percent of respondents indicated that they would have not taken the same trip if a HAB or bacterial warning was in effect at the site where they were intercepted. 46 percent of respondents would not have gone to any site if a bacterial warning was in effect at the site they visited, and similarly 42 percent would not have gone to any site if a HAB warning was in effect at the site they visited. For both types of water quality events, the percentage of respondents who indicated that they would have made the same trip gradually increased as the time since the event's lifting grew. However, roughly 24% of respondents still would not have made the same trip if a bacterial warning had been lifted 6 days before their trip, and roughly 20% would not have made the same trip in a similar HAB warning scenario.

Table 2.4: Average Contingent Behavior Response Percentages and Standard Errors

CB Scenario	I would have gone to the same beach. %	I would have gone to another beach. %	I would not have gone to any beach. %
Bac. warning- day of trip	**18.97**	**34.81**	**46.23**
	(1.32)	(1.62)	(1.69)
-Lifted 1 day before trip	**34.55**	**31.95**	**33.51**
	(1.62)	(1.58)	(1.60)
-Lifted 3 days before trip	**52.62**	**25.79**	**21.59**
	(1.69)	(1.48)	(1.39)
-Lifted 6 days before trip	**76.22**	**11.42**	**12.36**
	(1.44)	(1.08)	(1.10)
HAB warning- day of trip	**19.23**	**38.12**	**42.65**
	(1.33)	(1.65)	(1.68)
-Lifted 1 day before trip	**39.03**	**30.02**	**30.95**
	(1.66)	(1.56)	(1.56)
-Lifted 3 days before trip	**62.24**	**22.10**	**15.66**
	(1.64)	(1.40)	(1.23)
-Lifted 6 days before trip	**80.10**	**11.03**	**8.87**
	(1.34)	(1.06)	(0.95)
HAB warning- next beach along the shore	**56.29** (1.68)	**15.18** (1.22)	**28.52** (1.53)

At all warning attribute levels, fewer respondents would have made the same trip in a bacterial scenario compared to a HAB warning scenario. For each level of lifted warnings (1, 3, and 6 day-lifted warnings) we reject the null hypothesis of equality between the percentages of respondents who would make the same trip given a HAB or bacterial warning. However, the percentages of respondents who would have made the same trip if either a HAB or bacterial warning were currently in effect are not statistically different from one another. Consistent with findings from the first paper in this thesis, these results indicate that respondents in the sample are similarly averse to current HAB and bacterial events, but this aversion seems to linger more intensely and for a more sustained period after a bacterial event.

The results of our nested logit site-choice model are shown in Table 2.5. The choice of whether to take a trip (the participation nest) is modeled as a function of zip code-level demographics obtained from the American Community Survey 2018 five-year estimates. Our parameter estimates imply that, all else equal, potential beachgoers from zip codes with a higher median age are more likely to make a trip, as are potential beachgoers from zip codes with a higher percentage of college graduates. Beachgoers from zip codes with a higher share of white and Hispanic residents, as well as higher unemployment rates, are also more likely to make a trip. The estimated parameter on median income is positive and implies that potential beachgoers from zip codes with higher incomes have a lower probability of making a trip to these beaches, all else equal.

Table 2.5: Revealed Preference Recreation Demand Model Estimates

Nest	Variable	Coefficient	Std. Error[21]	95% Confidence Interval
Trip	Travel cost	-0.0072***	3.62E-05	(-0.0073, -0.0072)
	Dissimilarity coefficient	0.111***	5.16E-04	(0.109, 0.111)
No Trip	Median income (/10k)	0.078***	8.58E-04	(0.077, 0.080)
	Median age	-0.056***	2.7E-04	(-0.059, -0.058)
	% college graduate	-0.0054***	9.43E-05	(-0.0056, -0.0052)
	% unemployed	-0.031***	4.45E-04	(-0.032, -0.030)
	% white	-0.0098***	7.15E-05	(-0.0098, -0.0095)
	% Hispanic	-0.027***	9.51E-05	(-0.027, -0.026)

(***) denotes significance at the 1% level.
Estimated site constants are reported in Table 2.6.

In the trip nest, we estimate a negative and significant coefficient on the round-trip travel cost, indicating that a higher travel cost lowers the probability of choosing a site, all else equal. We also estimate a full set of J = 28 alternative specific constants, which are listed in Table 2.6. As discussed earlier, the dissimilarity coefficient τ reflects the degree of correlation between the alternatives in the trip nest. We estimate a value of τ 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 prices or site qualities change, the sites are closer substitutes for one another than the no-trip option.

We use the results of our site-choice model to examine the welfare effects of site closures. The disutility of closing a site j is equal to the expected maximum utility of the choice

[21] The reported standard errors and confidence intervals were obtained via bootstrap estimation on 127 replicate datasets. However, these estimates do not yet take into account the underlying variation in our trip estimates, and future efforts will account for this variation.

between the original set of *J* sites, less the expected maximum utility of the choice between the J-1 sites other than site *j*. As explained earlier, the measure is given by Equation (21) and produces the monetized value of lost surplus due to the closure of *j*.

For each site, we estimate the lost surplus value of site closures across a single recreation season, and the loss in trips that these closures would induce (Table 2.6). We also report each site's value per lost trip, which are more readily compared to results in the literature. Total seasonal welfare loss from the closure of a single beach ranges from $24,000 to $3,915,000 across each of the sites, with a trip-weighted average loss of $1,779,000. Value per lost trip across one season averages $16.34 in our sample of sites, and Detroit's Belle Isle has the largest value per lost trip at $19.48. Using a welfare computation for multiple site closures based on Equation (17), we calculate that the closure of all 28 beaches in our sample would induce roughly $208 million in welfare losses per year. While a closure of this magnitude is extremely unlikely to occur, and so policy analysis using this value would be unwise, this estimate illustrates the total recreational value of the public beaches in our sample area.

To illustrate how beachgoers make tradeoffs between environmental quality and the price of site access in the presence or absence of substitute sites, consider the estimated site ASCs from our site choice model (Table 2.6). A comparatively small ASC indicates a lower level of the unobserved environmental attributes which enter a given site's utility function, relative to the level of environmental attributes at other sites. To more readily compare ASCs across sites, the last column of Table 2.6 normalizes each constant relative to the lowest estimated ASC. The lowest ASC of any beach in the sample belongs to Showse Park Beach, a site in Vermillion, Ohio with a relatively small sandy area. This low ASC makes sense given Showse Park's size and proximity to larger, more sandy public beaches such as Main Street and Lakeview Park. Showse Park also has the smallest value per lost trip in the sample ($15.28).

Table 2.6: Site Closure Welfare Estimates

Site	Welfare loss from seasonal site closure	Lost trips due to site closure	Value per lost trip	ASC/site fixed effect	Normalized ASC
Walter & Mary Burke Park	$659,000	38,000	$17.27	-6.268	0.163
Lake St. Clair Metropark	$1,118,000	64,000	$17.41	-6.228	0.203
Belle Isle Beach	$3,014,000	155,000	$19.48	-6.126	0.305
Sterling State Park	$2,221,000	122,000	$18.21	-6.106	0.325
Luna Pier Beach	$389,000	25,000	$15.70	-6.274	0.157
Maumee - Erie Beach	$775,000	47,000	$16.44	-6.144	0.287
Maumee – Inland Beach	$250,000	16,000	$15.62	-6.264	0.167
Camp Perry Beach	$229,000	15,000	$15.53	-6.194	0.237
Port Clinton City Beach	$284,000	18,000	$15.58	-6.175	0.256
East Harbor State Park	$1,756,000	101,000	$17.42	-5.935	0.496
Nickel Plate Beach	$767,000	48,000	$16.10	-6.06	0.371
Old Woman Creek Beach	$93,000	6,000	$15.35	-6.3	0.131
Sherod Park Beach	$59,000	4,000	$15.31	-6.337	0.094
Main Street Beach	$463,000	29,000	$15.69	-6.118	0.313
Showse Park Beach	$24,000	2,000	$15.28	-6.431	0
Lakeview Park Beach	$650,000	41,000	$15.84	-6.075	0.356
Century Park Beach	$96,000	6,000	$15.34	-6.286	0.145
Veteran's Beach	$84,000	5,000	$15.33	-6.3	0.131
Huntington Beach	$1,137,000	70,000	$16.22	-6.039	0.392
Edgewater Park Beach	$3,915,000	215,000	$18.22	-5.937	0.494
Euclid State Park	$287,000	19,000	$15.46	-6.176	0.255
Sims Park Beach	$117,000	8,000	$15.34	-6.269	0.162
Headlands Beach St. Park	$1,410,000	86,000	$16.49	-5.952	0.479
Fairport Harbor Park Beach	$1,398,000	86,000	$16.27	-5.951	0.48
Geneva State Park	$1,154,000	71,000	$16.26	-5.926	0.505
Walnut Beach	$1,397,000	83,000	$16.92	-5.945	0.486
Lakeshore Park Beach	$311,000	20,000	$15.61	-6.114	0.317
Conneaut Beach	$1,343,000	76,000	$17.74	-5.939	0.492
Min	$24,000	2,000	$15.28		
Max	$3,915,000	215,000	$19.48		
Mean (trip-weighted)	$1,779,000	53,000	$16.34		

On the other hand, while Detroit's Belle Isle has the largest estimated value per lost trip ($19.48), its ASC is only the 14th largest among the 28 sampled beaches. These results indicate that while Belle Isle does not have the most desirable beach attributes to the average beach user, its closure would have the largest welfare effects. This result is likely attributable to the fact that Belle Isle is the only public beach in the city of Detroit, and accordingly has much higher baseline visitation than any other site in our sample due to the surrounding population density[22]. Additionally, Belle Isle's closest substitute sites, Lake St. Clair Metropark and Sterling State Park, are 24 and 48 miles away, and the absence of close substitutes likely also contributes to Belle Isle's high value. St. Clair Metropark and Sterling State Park exhibit a similar pattern, as both have high values per lost trip and low ASCs relative to the other sites in our sample.

While there are only 5 public beaches on the roughly 100 miles of shoreline which extend from the Michigan border to the northern tip of Lake St. Clair, Ohio's roughly 200-mile Erie coast has 23 public beaches. This denser spatial ordering of Ohio sites is reflected in the welfare estimates above. Edgewater Park Beach, East Harbor State Park Beach, and Conneaut Beach have the highest values per lost trip of all sites in Ohio, however the highest value among these three ($18.22 at Edgewater Park Beach) is still over a dollar less per lost trip than Belle Isle. All three sites have higher ASCs than Belle Isle, and so the most likely explanation for the relatively lower values of Ohio sites despite higher levels of unobserved environmental amenities is the dense clustering of substitute sites nearby. Edgewater Park can be most readily compared to Belle Isle given its location in downtown Cleveland, and its $18.22 value per lost trip estimate is likely influenced by the large number of Cleveland residents who use the site (Edgewater Park has the highest number of estimated lost trips in our sample).

[22] Indeed, Belle Isle is estimated to lose the second highest number trips across all sites, over 155,000, in the event of a seasonal closure.

The above welfare estimates offer important information about the value of Lake Erie and Lake St. Clair beaches. However, because HAB and bacterial events do not usually result in the closing of sites,[23] these estimates do not best reflect the welfare impacts of HABs and bacterial contamination in the region. To estimate these impacts, we use the disutilities identified by the contraction mapping procedure described earlier. Before doing so, we correct the initially estimated constants to account for the HAB and bacterial events which were observed during the 2019 recreation season.

If the contraction mapping was computed using the estimated constants without correction, this procedure would implicitly assume that the initial site-choice model was estimated using data from sites unaffected by HAB or bacterial warnings during the 2019 recreational season. However, this is not the case, as 21 of the 28 sites used in our analysis experienced at least one type of warning from May 27th to September 1st.[24] Given the purpose of this study and the regularity of HAB and bacterial warnings in the area, this complication is not unexpected. However, since this discrepancy can potentially influence the absolute magnitude of total welfare loss and lost trips, the ASCs are adjusted to a counterfactual level of "pristine" water quality before using the contraction mapping to identify the true disutility parameters associated with different HAB and bacterial scenarios.

For each site j in our analysis, we estimated an alternative-specific constant α_j which captured the effect of unobserved environmental quality attributes on site-specific utility. In the

[23] Across the 28 sampled sites, 115 HAB and bacterial events were reported on the Michigan and Ohio BeachGuard websites from May to August 2019. Of the 115 events reported, only 3 were closings and 112 were warnings.
[24] 115 total warnings were observed at these 21 sites during the season, according to Michigan BeachGuard and Ohio BeachGuard. 110 of these were bacterial warnings, and 5 were HAB warnings. Here, we only consider warnings directly attributed to observed bacterial contamination or algal blooms in the BeachGuard system. Warnings informed by predictive modeling are excluded from our analysis.

case of the 21 sites where HAB and bacterial warnings were observed during the 2019 season[25], α_j do not represent the counterfactual, unimpaired levels of environmental quality at each site in the absence of HABs and bacterial warnings. Let α_j^0 denote the unknown ASC for site *j* which captures this level of unobserved environmental quality in the absence of warnings. For the 7 sites where no warnings were issued in 2019, $\alpha_j^0 = \alpha_j$. For all 28 sites, we also obtain Δ_j^s, the contraction mapping adjustment to α_j which calibrates the site choice model to the pattern of demand observed in the CB responses for scenario *s*.

Suppose that site *j* only suffers from one type of warning during the season, the fraction of days in the season affected by a warning *s* is given by γ_j^s, and assume for the moment that beachgoers do not derive any disutility from a site with a recently-lifted warning. Further, let $\alpha_j^{s*} = \alpha_j^0 + \delta_j^{s*}$ denote the constant which results from adjusting the unknown "baseline" ASC α_j^0 by the quantity δ_j^{s*}, and simulates the effects of a season-long warning. In this case, the initially estimated "impaired" ASC α_j can be written as:

$$\begin{aligned} \alpha_j &= \left(1 - \gamma_j^s\right)\alpha_j^0 + (\gamma_j^s)\alpha_j^{s*} \\ &= \left(1 - \gamma_j^s\right)\alpha_j^0 + \left(\gamma_j^s\right)\left(\alpha_j^0 + \delta_j^{s*}\right) \\ &= \alpha_j^0 + \gamma_j^s \delta_j^{s*} \\ \therefore\ \alpha_j^0 &= \alpha_j - \gamma_j^s \delta_j^{s*} \end{aligned} \tag{22}$$

All terms on the right side of this final equation are known[26], except for δ_j^{s*}, the calibration adjustment to the baseline unimpaired ASC of site *j*, α_j^0. However, noting that $\alpha_j^0 = \alpha_j$ for the 7 unaffected sites, we can see that in these cases, the "true" calibration adjustment δ_j^{s*} is precisely equal to the known adjustment produced by the contraction mapping, Δ_j^s. Let the average of

[25] Defined as May 27th through September 1st, the length of the summer 2019 intercept survey.
[26] γ_j^s is obtained from the BeachGuard websites.

these calibration adjustments across the 7 unimpaired sites be denoted $\overline{\delta_U^{s*}}$. Then, for any site j which experienced a warning during the season, $\overline{\delta_U^{s*}}$can be used to estimate the baseline ASC α_j^0, as follows:

$$\alpha_j^0 = \alpha_j - \gamma_j^s \delta_j^{s*} \approx \alpha_j^0 = \alpha_j - \gamma_j^s \overline{\delta_U^{s*}} \tag{23}$$

This process is similarly expanded to account for the disamenity effects of recently lifted HAB and bacterial warnings. The adjusted baseline ASCs can then be fed back into the contraction mapping algorithm and welfare formulas to recover correctly scaled estimates of total welfare loss and lost trips for each HAB and bacterial scenario.

For each contingent behavior scenario s, we obtain σ, the proportion of respondents who indicated that they would have gone to the same site if the given scenario were in effect. For each site j and scenario s, the contraction mapping algorithm adjusts site j's ASC by Δ_j^s, a constant which replicates the pattern of demand predicted by the contingent behavior responses within the structural demand system. These individual ASC adjustments are listed in Table M.1 of Appendix M.

For each scenario, we compute the average of Δ_j^s across the J = 28 sites, weighted by predicted trips to each site, to obtain $\overline{\Delta^s}$**.** The outcome of the site adjustments from the contraction map allows us to produce estimates of seasonal welfare losses and lost trips for each site-scenario combination. Table 2.7 reports average welfare estimates for each HAB or bacterial scenario, weighted by predicted trips to each site, as well as the bootstrapped confidence intervals for these welfare estimates.

Table 2.7: Average ASC Adjustment and Trip-Weighted Average Welfare Loss, Across All Sites, for Each Water Quality Scenario

Water Quality Scenario	$\overline{\Delta^s}$	Seasonal welfare loss	Lost trips	Value per lost trip
Bacterial warning- day of trip	-0.206 (-0.22, -0.192)	$1,448,823 ($1,361,575, $1,551,253)	82,170 (77,167, 88,113)	$17.27 ($17.19, $17.33)
-Lifted 1 day before trip	-0.132 (-0.142, -0.123)	$1,172,656 ($1,097,839, $1,256,520)	65,286 (61,014, 70,044)	$17.57 ($17.50, $17.64)
-Lifted 3 days before trip	-0.081 (-0.09, -0.075)	$853,871 ($780,057, $932,242)	46,596 (42,388, 50,942)	$17.90 ($17.81, $17.96)
-Lifted 6 days before trip	-0.035 (-0.04, -0.031)	$434,521 ($373,109, $490,907)	23,137 (19,824, 26,200)	$18.32 ($18.24, $18.39)
HAB warning- day of trip	-0.203 (-0.219, -0.186)	$1,441,475 ($1,346,812, $1,521,045)	81,712 (76,248, 84,451)	$17.28 ($17.21, $17.34)
-Lifted 1 day before trip	-0.118 (-0.129, -0.109)	$1,096,386 ($1,022,130, $1,190,257)	60,742 (56,256, 66,285)	$17.65 ($17.56, $17.75)
-Lifted 3 days before trip	-0.06 (-0.067, -0.053)	$681,624 ($616,538, $756,165)	36,815 (33,165, 40,926)	$18.07 ($17.98, $18.17)
-Lifted 6 days before trip	-0.029 (-0.033, -0.024)	$363,875 ($310,308, $421,638)	19,299 (16,432, 22,426)	$18.38 ($18.31, $18.46)

These estimates represent the average welfare losses which would occur if each scenario were in effect for an entire summer recreational season. On average, a HAB or bacterial warning which affects the average site for an entire season is estimated to result in losses of about $17.30 per lost trip, and roughly $1.4 million in seasonal welfare losses.

Our estimates of seasonal welfare loss and lost trips behave as expected—current HAB and bacterial warnings result in higher welfare losses and more lost trips than day-old warnings, and so on. However, as the time since either type of warning grows, total estimated welfare losses decrease at a faster rate than lost trips, which causes our value per lost trip estimates to increase. The gap between value per lost trip for a current warning and a 6-day expired warning is relatively small in both cases (just over $1).

While our welfare estimates for season-long HAB and bacterial warnings are easy to interpret, it isn't clear what a "season-long 1-day lifted HAB warning" (for example) means in practice. In the next section, we develop a more easily interpretable method for using these estimates to simulate the temporal welfare impacts of observed warnings in 2019.

2.8: Simulation of 2019 Season

In addition to estimating the welfare losses associated with a full season of HAB and bacterial warnings, our results can be used to move from modeling the abstract notion of season-long warnings to simulating the effects of actual observed events. The Michigan and Ohio BeachGuard websites provide the number of warnings in effect at each site during the 2019 season, as well as the dates and durations of each warning. Once total seasonal welfare loss estimates are obtained for each HAB or bacterial scenario at each site, these estimates can be prorated across a season to match the number of days with an observed warning (or days within 1, 3, or 6 days after a warning) at each site.

Appendix L summarizes the bacterial and HAB warnings observed during the 2019 season. Dividing each seasonal welfare loss estimate by the number of days in the season produces a rough estimate of the per-day welfare loss of each scenario. By multiplying each of these estimates by the number of days in which the respective warning scenario is in effect and summing these products, we recover an estimate of the total recreational welfare loss caused by the observed HAB and bacterial warnings during the 2019 season. We treat days which fall 2 days after the lifting of a warning as "1-day lifted", and days which fall 4 and 5 days after the lifting of a warning as "3-day lifted".[27] By executing this process on 127 bootstrapped datasets, we generate empirical confidence intervals for this simulation of the 2019 season's welfare losses. The results of this estimation process are shown below in Table 2.8.

[27] This welfare loss is calculated assuming that the welfare effects of a 2-day lifted warning are the same as a 1-day lifted warning, and likewise the effects of a 4-5 day lifted warning are the same as a 3-day lifted warning, but it assumes no effect after 6 days. An alternative approach that maintained the assumption of no losses after 6 days, losses for 2-day lifted warnings = 3-day lifted warnings and 4-5 day lifted warnings = 6-day lifted warnings found welfare losses totaling 93% of the above approach. A linear interpolation of the values from these two approaches totaled 96% of the above approach.

Table 2.8: Simulation of Welfare Losses Attributable to Bacterial and HAB Warnings during the 2019 Recreation Season

Simulated Scenario	Welfare loss attributable to observed warnings in 2019
All bacterial and HAB warnings, including welfare losses from up to six days following a warning	$5,802,336 ($5,461,049, $6,184,385)
All bacterial and HAB warnings, only accounting for day-of welfare losses	$3,848,011 ($3,619,996, $4,111,074)
% Understatement of not accounting for lagged welfare effects	33.68 (32.91, 34.67)
All HAB warnings, but no bacterial warnings, including welfare losses from up to six days following a warning	$854,585 ($787,797, $928,934)
All HAB warnings, but no bacterial warnings, only accounting for day-of welfare losses	$750,408 ($689,515, $818,426)
All bacterial warnings, but no HAB warnings, including welfare losses from up to six days following a warning	$4,947,751 ($4,636,671, $5,283,923)
All bacterial warnings, but no HAB warnings, only accounting for day-of welfare losses	$3,097,603 ($2,894,187, $3,305,886)

Note: 95% confidence intervals are in parentheses.

We find a mean total seasonal welfare loss of about $5.8 million during the 2019 recreational season which can be attributed to HAB and bacterial warnings[28]. This information can be used by policy makers to begin to quantify the effects of *E. coli* and HAB warnings on public beach recreation. This amounts to roughly 2.8% of the total annual value of recreation at these beaches. Eliminating warnings would provide benefits to beachgoers as well as the nearby businesses that benefit from their patronage due to the additional trips that would be taken.

[28] See footnote 27 for robustness of this method.

We have also established that the recreational welfare effects of bacterial and HAB warnings do not immediately dissipate over time. There are two important implications of this finding. First, any warning, even if only a day, has longer-term consequences for recreation. This finding heightens the need to develop policies that work to eliminate warnings themselves, not just the length of warnings. Second, and consequentially for welfare measurement, the failure to account for this "lag" effect understates the resulting welfare estimates. To illustrate the effect of ignoring recently lifted warnings, we recalculate the 2019 season's welfare losses using only days on which a warning was in effect and find a mean total welfare loss of about $3.8 million. This estimate is roughly 34% lower than our initial estimate that accounted for "lag" effects, which explicitly illustrates the importance of accounting for the full costs of HAB and bacterial warnings in policymaking and cost-benefit analysis. Additionally, accounting for the disamenity effects of recently lifted warnings, we find that bacterial warnings are responsible for 85% of total 2019 welfare losses (roughly $4.95 million), while HAB warnings are responsible for 15% of seasonal welfare losses (roughly $855,000). These estimates indicate that while HAB events often command significant media attention and possess a visual aspect that bacterial contamination events do not, bacterial contamination currently represents a much larger proportional threat to beach recreation in the region.

While this information is useful from a policy standpoint, it is also worthwhile to note that the magnitude of welfare losses attributable to bacterial contamination is driven by the large number of bacterial warning days in the 2019 season, relative to HAB warning days. Rather than relying solely on absolute welfare loss estimates, we obtain standardized measures of the disamenity value of HAB and bacterial warnings to more reliably compare how beachgoers value the presence of these warnings. The mean day-of welfare loss attributable to warnings in the 2019 season is about $3 million for bacterial contamination and $750,000 for HABs; likewise, 475 days of the season were directly affected by a bacterial warning in 2019, and 73 were directly affected by a HAB warning. The quotient of these values produces a standardized "loss per beach-day" value for each type of warning of $6,500 per day for bacterial warning events and $10,300 per day for HABs events. Despite the larger share of total losses attributable to bacterial warnings, these standardized values indicate that beachgoers reap much larger disutility from the sites where HAB warnings were effect, as opposed to the ones with a bacterial warning in effect.

2.9: Conclusion

In this paper, we have shown that the welfare costs of water-borne health hazard warnings are high and persist for at least six days after warnings are lifted. Our research contributes to the relatively small number of studies that estimate the economic value of Great Lakes recreation and is one of the few studies to use contingent behavior data embedded within a revealed preference model to value environmental quality at freshwater beaches. This work also contributes to the limited number of studies estimating welfare impacts of freshwater HABs and bacterial contamination, events projected to worsen in frequency and intensity under global climate change. While prior studies have used beach closings as a proxy for season-long HABs, we estimate the welfare effects of HAB events when beaches stay open, which more accurately reflects observed beach management.

We utilized a combined stated preference and revealed preference approach to estimate the welfare impacts of water quality warnings that are common in the western Lake Erie Basin. Revealed preference data on observed trips to 28 public beaches was collected using an intercept survey during the summer of 2019. Each randomly selected respondent was recruited for an online stated preference survey that included contingent behavior questions asking about stated travel behavior in the face of possible harmful algal bloom (HAB) and bacterial warnings. The RP data was used to create a zonal dataset that treated each observed origin zip code as a representative agent, and inverse probability weights were created to estimate trips from each origin zip code to each destination site. We estimated a repeated random utility zonal site choice model on this dataset and were able to isolate the welfare effects of seasonal site closures, finding an average loss of $16.34 per lost trip across all sites. The model also produced a full set of alternative-specific constants, which capture the influence of unobserved environmental quality attributes. After estimating the site-choice model, we identified the disutilities of HAB and bacterial warnings using a contraction mapping algorithm that calibrated the ASCs until the predicted pattern of demand matched the pattern implied by the stated preference responses to our follow-up survey. This calibrated model was used to examine the welfare impacts of season-long HAB and bacterial warnings, finding that these scenarios would each result in welfare losses of $1.4 million at the average site in our sample. We also used our seasonal welfare estimates to show that the observed HAB and bacterial events in the western Lake Erie Basin caused over $5.8 million in losses during the 2019 season, and we demonstrated that not accounting for the disamenity effects of recently lifted warnings would underestimate these damages by roughly 34 percent. Additionally, we find that 85% of the estimated 2019 welfare losses (4,900,000) are attributable to bacterial events, while the 2019 HABs are responsible for 15% of seasonal welfare losses ($855,000). However, when these estimates are standardized by dividing by the number of days on which each type of warning was in effect, we find that beachgoers reap more than three times as much daily disutility from the sites that had a HAB warning in effect, compared to sites that had a bacterial warning.

These results can aid state agencies and policy makers in understanding the full costs of current freshwater HAB and bacterial events, especially as both are projected to increase as a direct result of climate change. Our results are descriptive of the 2019 recreation season that was marked by high water levels which may have affected overall visitation and that was a relatively mild HAB season relative to years like 2011 and 2014. Accordingly, our results serve as a rough lower bound estimate of the yearly recreational welfare impacts to beachgoers of HAB and bacterial warnings. Without serious investment in runoff control technology or policy change, the welfare impacts of these events will likely continue to grow. In planning for the future, government agencies need improved understanding of the discounted future benefits resulting result from the up-front costs of environmental protection. Accordingly, future interdisciplinary research can build on our work by examining how the economic costs of point and non-point source water pollution will likely behave over time, and this dynamic consideration may also apply to other pollution costs such as non-use values. These dynamic cost estimates can then serve as empirical benchmarks for governments to use when making water quality policy in the face of a warming world.

APPENDICES

APPENDIX A: Intercept Survey Instrument

The survey below was read to Michigan beachgoers who agreed to participate in a survey about their beach visit, and who indicated they were over 18 years of age. This version of the survey was administered to beachgoers at two public Lake St. Clair beaches, Lake St. Clair Metropark and Walter & Mary Burke Park Beach, as well as Belle Isle Beach in Detroit. The version of the intercept survey administered to beachgoers at the other 26 beaches in our sample was essentially identical to this version.

To ensure that potential respondent selection was unbiased, interviewers approached every third beachgoer and asked if they would be willing to participate in the survey. Interviewers read questions to each respondent from the interviewer's mobile Qualtrics survey app, and then responses were recorded by the interviewer.

Figure A.1: Lake St. Clair and Belle Isle Intercept Survey

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Select name of interviewer.

- Interviewer 1 Name
- Interviewer 2 Name
- Other (enter name)

Initial contact {Read to potential respondent}

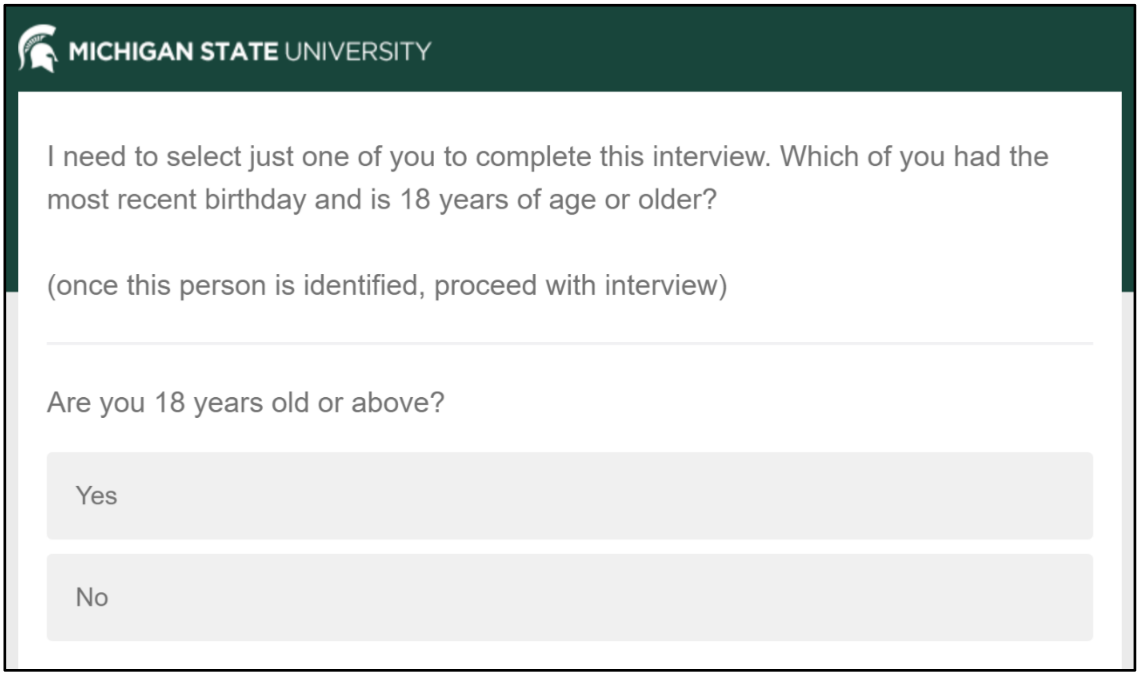
Hi, I work with Michigan State University and I'm conducting a research study on travel and tourism to Lake Erie and Lake St. Clair beaches for a study that will help beach managers serve visitors. Your participation in this research study is voluntary and all information is confidential. This survey take less than 5 minutes.

(If respondent asks more about survey/requests more info)
This information sheet gives your rights as a research subject. (hand info sheet to respondent)

Would you be willing to participate in this interview?

- Yes
- No

Figure A.1: (cont'd)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I need to select just one of you to complete this interview. Which of you had the most recent birthday and is 18 years of age or older?

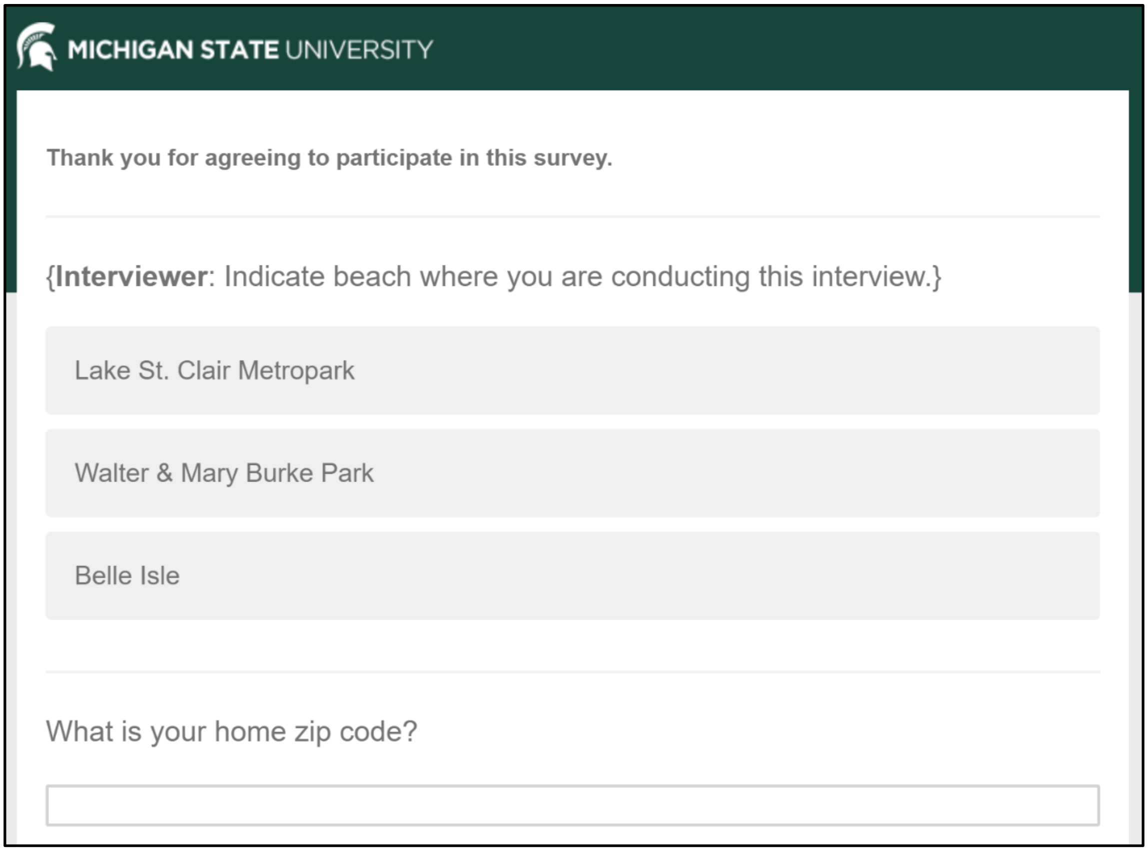
(once this person is identified, proceed with interview)

Are you 18 years old or above?

Yes

No

Figure A.1: (cont’d)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Thank you for agreeing to participate in this survey.

{**Interviewer**: Indicate beach where you are conducting this interview.}

- Lake St. Clair Metropark
- Walter & Mary Burke Park
- Belle Isle

What is your home zip code?

Figure A.1: (cont'd)

How many people came to the beach in the same car with you today? Please consider only the people who came in the same car as you, even if your group is bigger.

- 1
- 2
- 3
- 4
- 5+ (enter number)

What time did you get here?

What time do you plan to leave?

Figure A.1: (cont'd)

What is your age?

18-25

26-35

36-45

46-55

56-65

65+

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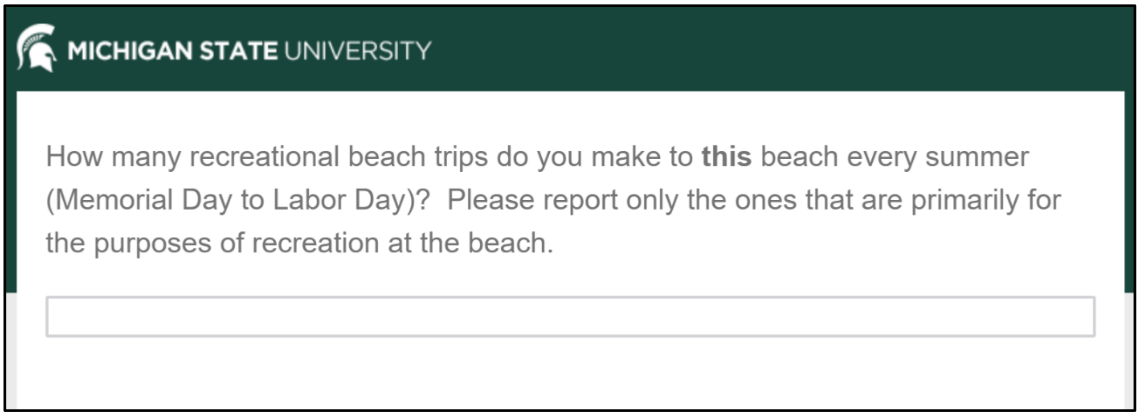
Is recreation the primary reason for your trip to the beach today? Consider your trip as the time you left home to the time you will return to your home.

Yes

No

Figure A.1: (cont'd)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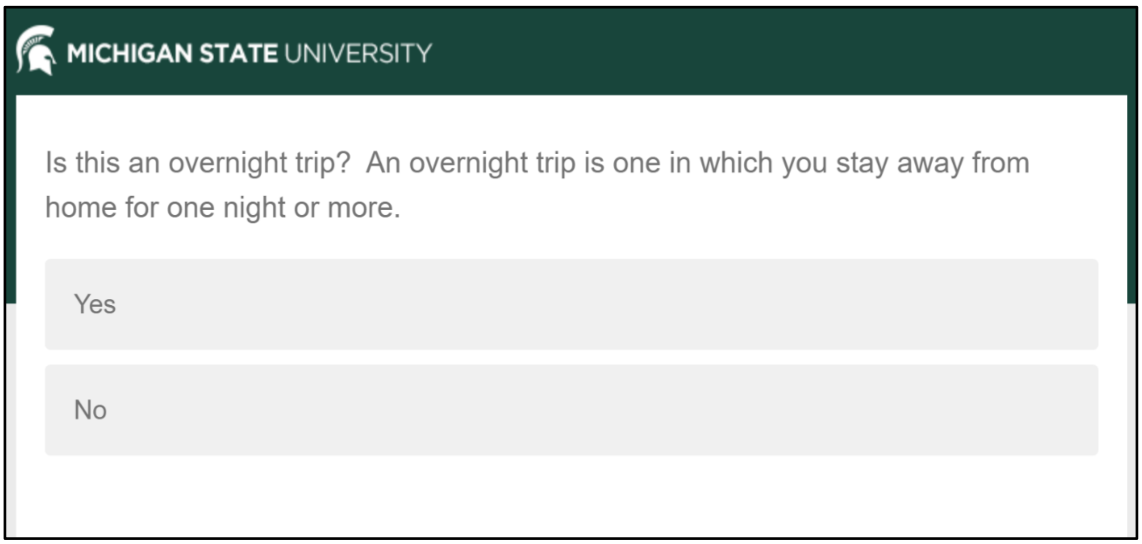
How many recreational beach trips do you make to **this** beach every summer (Memorial Day to Labor Day)? Please report only the ones that are primarily for the purposes of recreation at the beach.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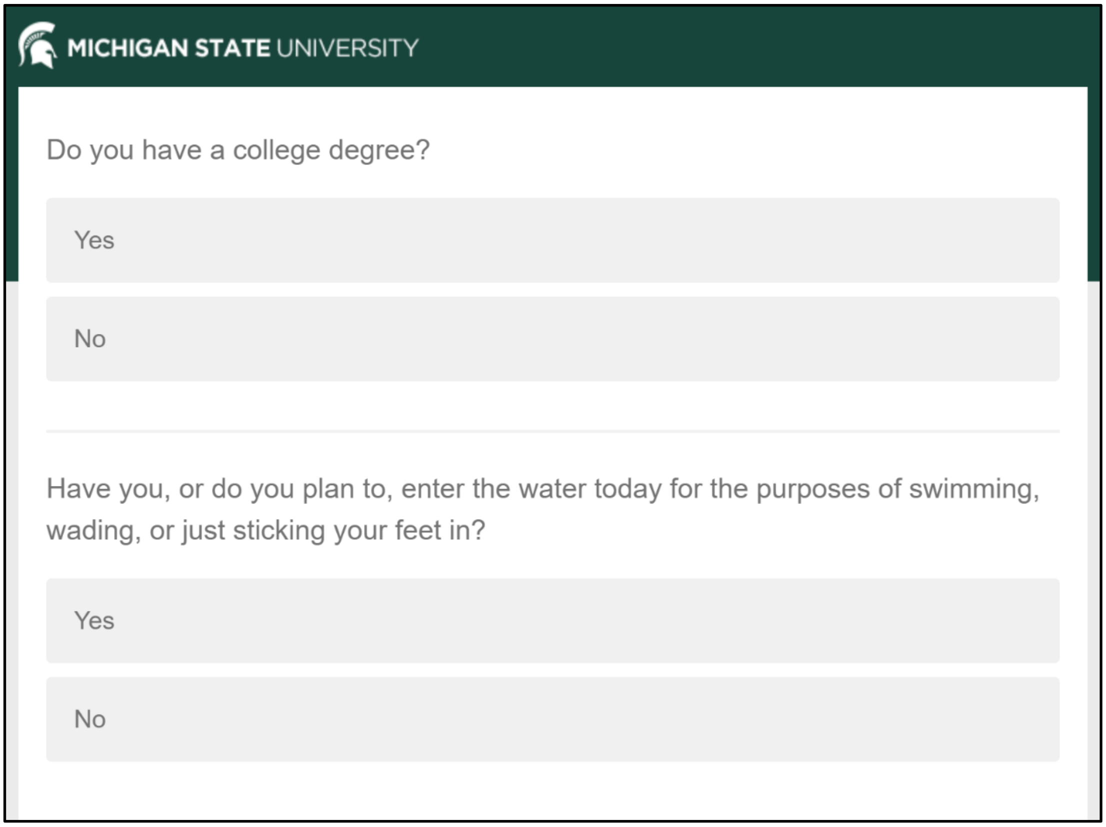
Is this an overnight trip? An overnight trip is one in which you stay away from home for one night or more.

Yes

No

Figure A.1: (cont'd)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Do you have a college degree?

Yes

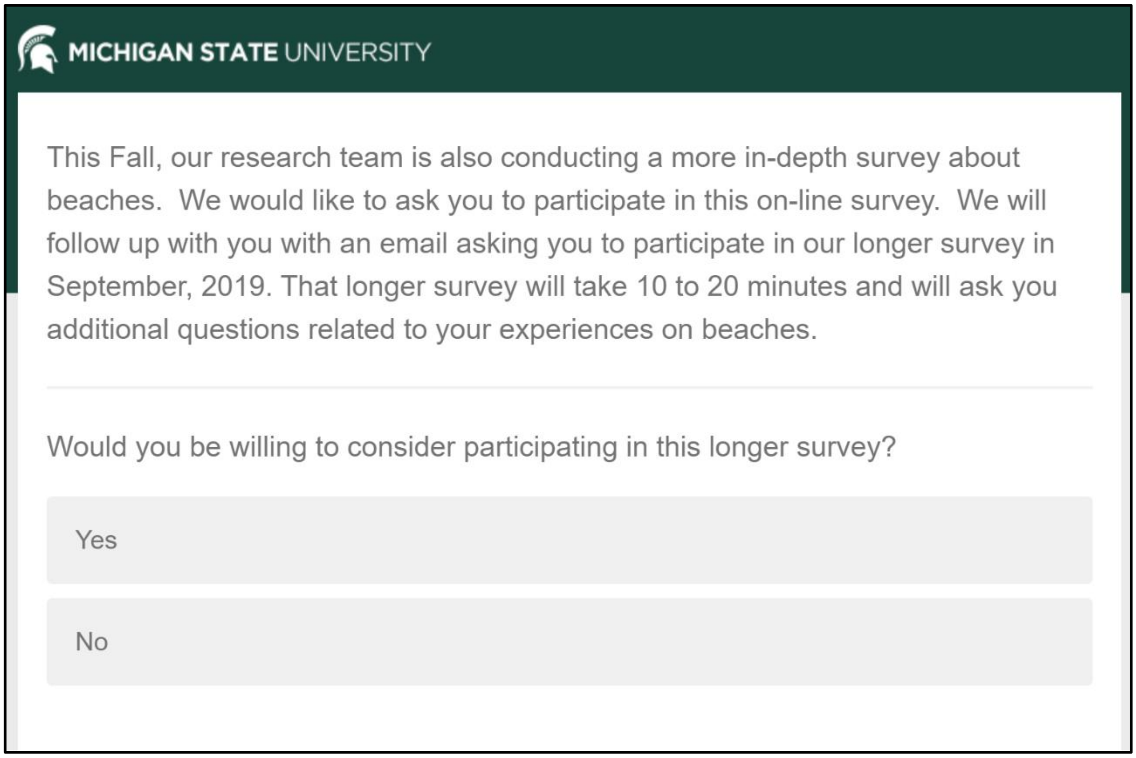
No

Have you, or do you plan to, enter the water today for the purposes of swimming, wading, or just sticking your feet in?

Yes

No

Figure A.1: (cont'd)



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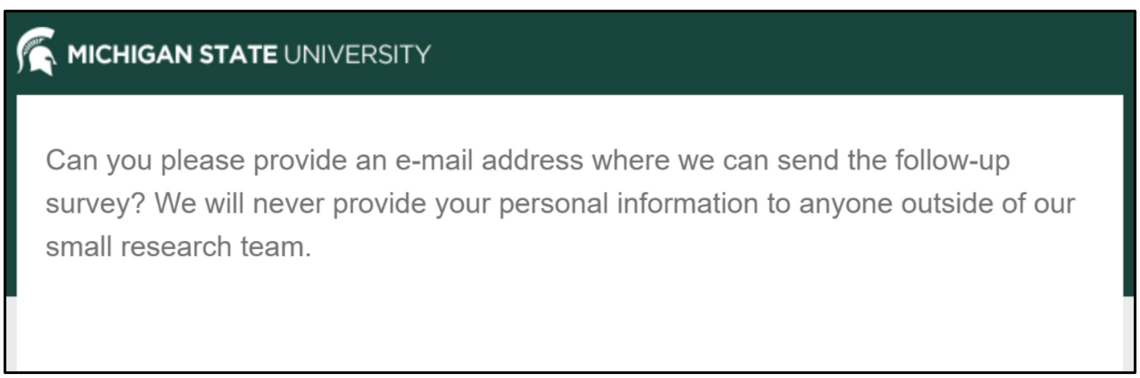
This Fall, our research team is also conducting a more in-depth survey about beaches. We would like to ask you to participate in this on-line survey. We will follow up with you with an email asking you to participate in our longer survey in September, 2019. That longer survey will take 10 to 20 minutes and will ask you additional questions related to your experiences on beaches.

Would you be willing to consider participating in this longer survey?

Yes

No



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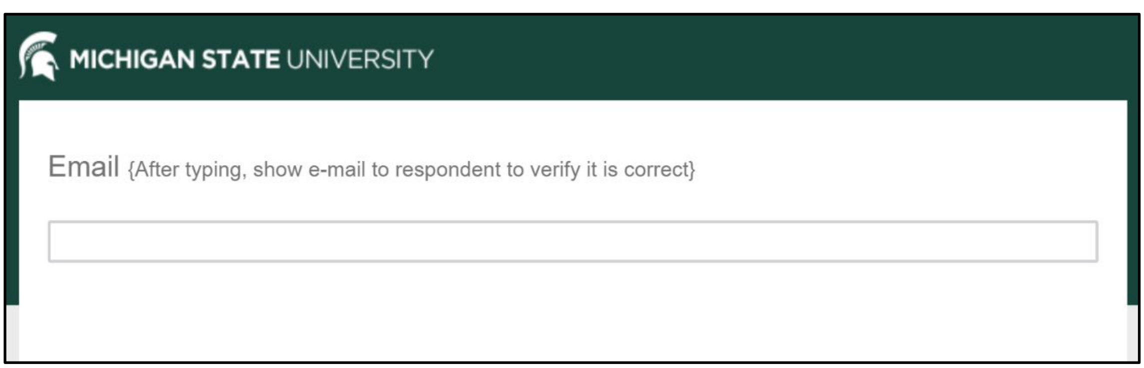
Can you please provide an e-mail address where we can send the follow-up survey? We will never provide your personal information to anyone outside of our small research team.



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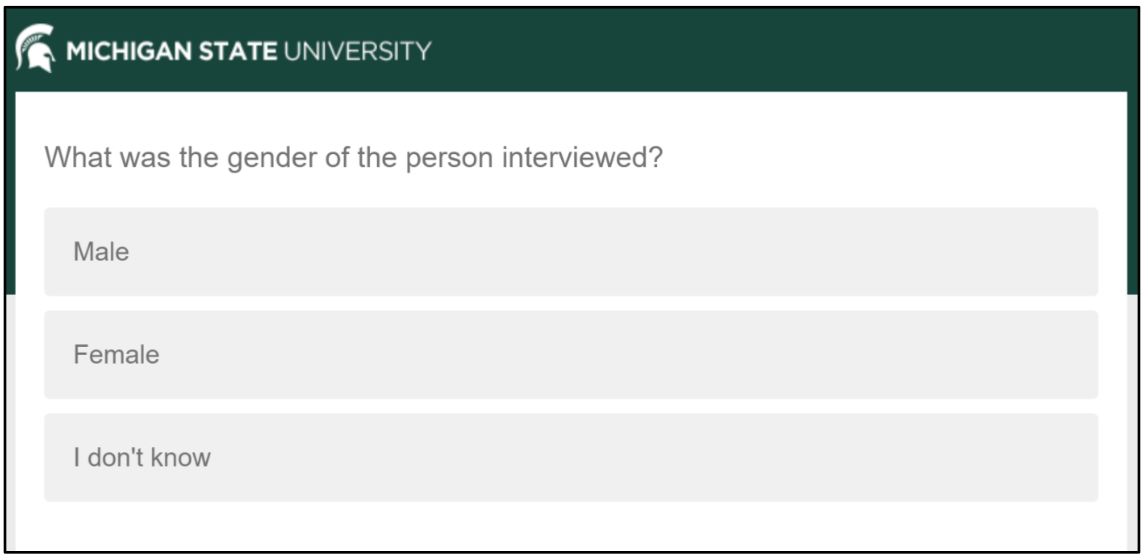
Email {After typing, show e-mail to respondent to verify it is correct}

Figure A.1: (cont'd)



APPENDIX B: Online Follow-Up Survey

The following survey was sent to Ohio and Michigan beachgoers who provided their emails during the intercept survey and indicated they would be willing to participate in the follow-up. Each follow-up instrument was specifically written to show the individual site where the respondent was interviewed; in this example the site has been specified as Belle Isle Beach. Similarly, the intercept year in this example has been specified as 2019. In the follow-up instrument, each respondent was shown 5 choice situations as part of the discrete choice experiment. For the sake of brevity, only one choice occasion is presented here. Individuals intercepted by the Ohio teams were send a version branded by Ohio State University.

Figure B.1: Online Follow-Up Survey

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Great Lakes Beach Survey

Participant Information and Consent Form

You are being asked to participate in a research study about Great Lakes beaches being conducted at Michigan State University. You must be at least 18 years old to participate. The research study takes most people about 10 to 15 minutes to complete.

The study results will be shared with beach managers so they can better understand people's views and meet people's needs.

Participation is completely voluntary. You have the right to say no. You may choose not to answer specific questions or to stop participating at any time. Any responses you provide are confidential.

By starting the survey, you indicate your voluntary agreement to participate.

I consent to survey

Questions or concerns:

If you have questions or concerns about this study, please contact Professor Frank Lupi, Michigan State University, Justin S. Morrill Hall of Agriculture, 446 West Circle Drive, Room 205, East Lansing, MI 48824, lupi@msu.edu, 517-432-3883.

If you have questions or concerns about your role and rights as a research participant or would like to register a complaint about this study, you may contact, anonymously if you wish, the Michigan State University's Human Research Protection Program at 517-355-2180, or e-mail irb@msu.edu or regular mail at 4000 Collins Road, Suite 136, Lansing, MI 48910.

Figure B.1: (cont.d)

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Your perceptions of beach attributes

Thank you for participating in this survey! We are going to ask about your perceptions of certain attributes of **Belle Isle Beach**, where we interviewed you in **2019.**
Attributes of **Belle Isle Beach** that we would like you to consider are:

- sand quality
- water clarity, and
- crowding.

Under each attribute, we have described different possible levels of the attribute. Based on your past visits to this beach, please select the level that best describes this beach.

Figure B.1: (cont.d)

Sand Quality

The levels of sand quality are:

Mostly Sand	Half Sand/Half Pebbles	Mostly Pebbles
> 75% smooth sand with < 25% pebble, rock, or shells.	About 50% sand and 50% pebble, rock, or shells.	< 25% smooth, white sand with >75% rock, pebble, or shells.
		

1. Based on your past visits to Belle Isle Beach, please select the level that best describes the sand quality at this beach.

- Mostly Sand
- Half Sand & Half Pebbles
- Mostly Pebbles

Figure B.1: (cont.d)

Water Clarity

The levels of water clarity are:

- **Clear** - you are able to see your feet from the surface when standing in 4 feet of water.
- **Somewhat murky** - you are unable to see your feet in water deeper than 1-2 feet.
- **Very murky** - you are unable to see your feet in 6-12 inches of water.

2. Based on your past visits to Belle Isle Beach, please select the level that best describes water clarity at this beach.

Clear

Somewhat Murky

Very Murky

Crowding

The levels of crowding are:

- **Not crowded** - you are able to find many spots to sit at this beach.
- **Somewhat crowded** - there are lots of people, but you are able to find a spot to sit at this beach.
- **Very crowded** - there are so many people on the beach, it is difficult to find a spot to sit.

3. Based on your past visits to Belle Isle Beach, please select the level that best describes the crowding at this beach.

Never Crowded

Somewhat Crowded

Very Crowded

Figure B.1: (cont.d)

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The tables below list popular Michigan and Ohio beaches along the shores of Lake Erie and Lake St. Clair. In the tables, please **indicate which beaches you're familiar with, and how many visits you took to each beach in 2019.**

If you have heard about a beach, but have never personally been there, please mark "familiar". If you are unsure about a beach, feel free to use the interactive map included between the tables.

Michigan Beaches

	Check if you are familiar with this beach.	Number of visits to this beach in 2019
(1) Belle Isle Beach (Wayne Co, MI)	☐	
(2) St. Clair Metropark (Macomb Co, MI)	☐	
(3) Walter & Mary Burke Park Beach (Macomb Co, MI)	☐	
(4) Sterling State Park (Monroe Co, MI)	☐	
(5) Luna Pier Beach (Monroe Co, MI)	☐	

Figure B.1: (cont.d)

Interactive map of beaches: To zoom in and out, use the icon in the top left corner of the map. To move the map, click and drag with your mouse.

<u>Ohio Beaches on Lake Erie</u>

	Check if you are familiar with this beach.	Number of visits to this beach 2019
(6) Maumee Bay State Park (Inland Beach) (Lucas Co, OH)	☐	
(6) Maumee Bay State Park (Erie Beach) (Lucas Co, OH)	☐	
(7) Camp Perry (Ottawa Co, OH)	☐	
(8) Port Clinton (Ottawa Co, OH)	☐	
(9) East Harbor (Ottawa Co, OH)	☐	
(10) Nickel Plate (Erie Co, OH)	☐	
(11) Old Woman Creek (Erie Co, OH)	☐	
(12) Sherod Park (Erie Co, OH)	☐	
(13) Main Street (Erie Co, OH)	☐	
(14) Showse (Erie Co, OH)	☐	
(15) Lakeview Park (Lorain Co, OH)	☐	
(16) Century (Lorain Co, OH)	☐	
(17) Veteran's (Lorain Co, OH)	☐	

Figure B.1: (cont.d)

(18) Huntington (Cuyahoga Co, OH)	☐	
(19) Edgewater Park (Cuyahoga Co, OH)	☐	
(20) Euclid (Cuyahoga Co, OH)	☐	
(21) Sims (Cuyahoga Co, OH)	☐	
(22) Headlands (Lake Co, OH)	☐	
(23) Fairport Harbor (Lake Co, OH)	☐	
(24) Walnut (Ashtabula Co, OH)	☐	
(25) Geneva State Park (Ashtabula Co, OH)	☐	
(26) Lakeshore Park (Ashtabula Co, OH)	☐	
(27) Conneaut (Ashtabula Co, OH)	☐	

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Water Quality at Michigan & Ohio Beaches

Harmful algal blooms are large masses of plant-like matter that grow in lakes and streams, and under certain conditions, emit toxins that can be dangerous to humans into the water. Harmful algal blooms are different from common lake plants or weeds you may find drifting in the water on a typical beach trip. Harmful algal blooms are caused by a certain weather conditions combined with agricultural nutrient pollution, and are most likely to occur in Lake Erie in the late summer in the Western Basin, off the northwest coast of Ohio and east coast of lower Michigan.

Harmful algal blooms (also referred to as HABs) can have the following effects.

HABs can:

- Produce odor
- Turn the contaminated body of water a neon-green color.
- Emit toxins into the water that can make humans very sick.
- Poison pets or make pets sick if they come in contact with affected water
- Make recreation areas, such as public beaches, very unpleasant, and possibly unsafe.

Figure B.1: (cont.d)

Below are two photos of a HAB in western Lake Erie, taken from the shore.

4. Have you encountered an algal bloom during a beach trip in the past two years?

Yes, I have encountered an algal bloom during a beach trip in the past two years.

No, I have not encountered an algal bloom during a beach trip in the past two years.

Figure B.1: (cont.d)

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Posted signs at beaches

Warning signs recommending against swimming may be posted at beaches for multiple reasons related to unsafe swimming conditions. These conditions may include harmful algal blooms, bacteria contamination, or other conditions deemed unsafe by the local beach manager. In some cases, beaches may be closed if swimming conditions are considered to be significantly unsafe.

A harmful algal bloom warning is issued for a beach if the level of toxins resulting from the harmful algal bloom gets too high at that beach. This indicates that the water at the affected beach is unsafe, and that people should avoid all contact with the water.

- In Ohio, these warnings are called Elevated Recreational Public Health Advisories, issued by the Ohio Department of Health. The advisory is posted on the public Ohio BeachGuard website, and signs are posted at the affected beach.
- In Michigan, these warnings are issued by local health departments, and are made available to the public on the Michigan BeachGuard website. Signs may also be posted at the affected beach.

5. Have you ever seen a harmful algal bloom sign posted at a beach you were visiting?

Yes, I have seen a harmful algal bloom warning sign posted at a beach I was visiting.

No, I have not seen a harmful algal bloom warning sign posted at a beach I was visiting.

Figure B.1: (cont.d)

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We are interested in your experiences related to harmful algal blooms off the coast of Michigan and/or Ohio.

6. In the past two years, have you ever ...

	Yes	No
... decided not to go to the beach because you knew it was closed due to a harmful algal bloom?	○	○
... driven to a beach on Lake Erie or Lake St. Clair, found there was a harmful algal bloom warning at that beach, and then left?	○	○
... driven to a beach on Lake Erie or Lake St. Clair, found out there was a harmful algal bloom warning at that beach, and then went to another beach?	○	○
... heard of a person getting sick due to exposure to harmful algal blooms?	○	○
... heard of a person whose pet got sick due to exposure to harmful algal blooms?	○	○
... used the Michigan BeachGuard and/or Ohio BeachGuard websites to learn about water quality before going to a Lake Erie or Lake St. Clair beach, because you were concerned about harmful algal blooms at that beach?	○	○
... viewed the NOAA Lake Erie Harmful Algal Bloom Bulletin, released twice weekly during active algal blooms (typically, July – October)?	○	○

Figure B.1: (cont.d)

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***E. coli* contamination**

E. coli is a type of bacteria that can be found in lakes, rivers and streams. Sources of *E. coli* contamination in bodies of water include agricultural runoff and overflow from wastewater treatment and sewer systems.

Contact with water contaminated by high levels of *E. coli* can cause the following symptoms:

- gastrointestinal illness
- skin, ear and eye infections
- stomach cramps
- diarrhea, nausea, and vomiting
- low-grade fever

---

7. Have you ever seen news reports of people getting sick due to *E. coli* contamination in bodies of water?

Yes, I have seen reports of people getting sick due to *E. coli* contamination in bodies of water.

No, I have not seen reports of people getting sick due to *E. coli* contamination in bodies of water.

Figure B.1: (cont.d)

Local and state environmental agencies routinely test bodies of water for unsafe levels of bacterial contamination. If the level of *E. coli* bacteria gets too high at a beach, an advisory is issued for that beach. During an advisory, children, the elderly, and people in ill health or with weak immune systems should avoid contact with the affected water.

In this case, signs similar to the one below may be posted at the affected beach. The states of Michigan and Ohio both maintain BeachGuard websites, where the public can access information about current *E. coli* advisories.

An advisory sign posted at Maumee Bay State Park in Ohio, during an E. coli contamination event

8. Have you ever seen a sign indicating high levels of bacterial contamination posted at a beach you have visited?

Yes, I have seen a bacterial contamination sign at a beach I have visited.

No, I have not seen a bacterial contamination sign at a beach I have visited.

Figure B.1: (cont.d)

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Changes at the Beach You Visited (Belle Isle Beach)

In this section, we will describe several scenarios, each with different environmental conditions at **Belle Isle Beach**. For each scenario, think back to your trip to Belle Isle Beach on June 22nd, 2019, and **consider if you would still have gone to Belle Isle Beach on that day under the given conditions.**

Suppose that, other than the changes we describe, nothing else has changed at Belle Isle Beach. Please consider the changes carefully. Your answers are very important to us!

1. Please read the scenarios described in the first column, and then **indicate if you still would have gone to Belle Isle Beach under the given conditions.**

"I would have gone to another beach" in the second column refers to any of the 27 Ohio and Michigan beaches you were asked about earlier in this survey. A map of these beaches is included below the table. Click here to see a list of the beaches we asked you about.

	Yes, I would have made the same trip.	No, I would have gone to another beach.	I would not have gone to any beach on that day.
Would you have made the same trip to Belle Isle Beach if ...			
... a harmful algal bloom warning was issued at Belle Isle Beach one week before your trip but was lifted 1 day before your trip?	○	○	○
... a harmful algal bloom warning was issued at Belle Isle Beach one week before your trip but was lifted 3 days before your trip?	○	○	○
... a harmful algal bloom warning was issued at Belle Isle Beach one week before your trip but was lifted 6 days before your trip?	○	○	○
... a bacterial advisory was issued at Belle Isle Beach one week before your trip but was lifted 1 day before your trip?	○	○	○
... a bacterial advisory was issued at Belle Isle Beach one week before your trip but was lifted 3 days before your trip?	○	○	○
... a bacterial advisory was issued at Belle Isle Beach one week before your trip but was lifted 6 days before your trip?	○	○	○

Figure B.1: (cont.d)

Would you have made the same trip to Belle Isle Beach if...

	Yes, I would have made the same trip.	No, I would have gone to another beach.	I would not have gone to any beach on that day.
... a harmful algal bloom warning was issued at Belle Isle Beach on the day you were interviewed.	○	○	○
... a harmful algal bloom warning was issued for the next beach along the shore from Belle Isle Beach on the day you were interviewed, but no warning was issued for Belle Isle Beach?	○	○	○
... a bacterial advisory was issued at Belle Isle Beach on the day you were interviewed.	○	○	○

Figure B.1: (cont.d)

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Your Preferences Toward Different Beach Attributes

This section asks about your preferences for various beach attributes. We will present five scenarios, each asking you to consider a trip to two possible beaches along the shore of Lake St. Clair or Lake Erie. For each scenario, we would like you to consider which beach you would prefer to visit, including the possibility of taking no trip at all.

The alternative beach trips will vary in several characteristics, such as sand quality, water quality, distance from your house to each beach, and whether or not a harmful algal bloom or E. coli advisory has been recently issued for the beach.

We know that it may be difficult to compare the one-way driving distances in the following scenarios, so we have included a map with one-way driving routes from Toledo, OH to four popular area beaches as a frame of reference. The routes and their distances are:

- Toledo to Maumee Bay State Park: **12 Miles**
- Toledo to Belle Isle Beach: **60 Miles**
- Toledo to Edgewater Park Beach: **110 Miles**
- Toledo to Conneaut Beach: **180 Miles**

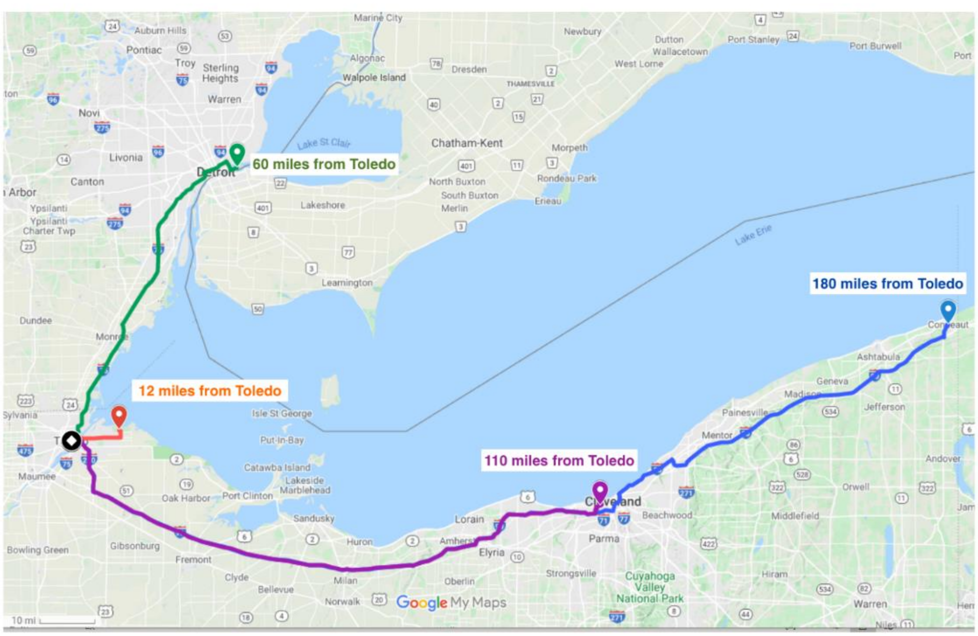

Figure B.1: (cont.d)

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Consider the two beaches in each table below, each with different levels of common beach attributes like sand quality and water clarity. (Click here for a reminder of what these attribute levels mean.)

Assume that these are the only two beaches available to visit, and if you do not visit one, you will not visit any beach on that day.

Scenario 1 of 5

Attribute	Beach A	Beach B
Sand quality	Mostly sand 	Mostly pebbles 
Presence of harmful algal bloom warning	A harmful algal bloom warning was issued for this beach a week before your trip, but was lifted 3 days before your trip.	A harmful algal bloom warning was issued for this beach a week before your trip, but was lifted 6 days before your trip.
Presence of bacterial advisory	A bacterial advisory was issued for this beach a week before your trip, but was lifted 6 days before your trip.	There is not a bacterial advisory at this beach, and there have not been any bacterial advisories here this season.
Water clarity	Clear	Somewhat murky
Crowding on the beach	Very crowded	Not crowded
Distance to beach (in miles)	**30 miles**	**70 miles**

1. Based on the beach characteristics in the table above, which beach would you choose to visit?

- I would choose to visit Beach A
- I would choose to visit Beach B
- I would not visit any beach that day

2. Out of the three options above, which is your least preferred?

- Visiting Beach A is my least preferred option.
- Visiting Beach B is my least preferred option.
- Not visiting any beach is my least preferred option.

Figure B.1: (cont.d)

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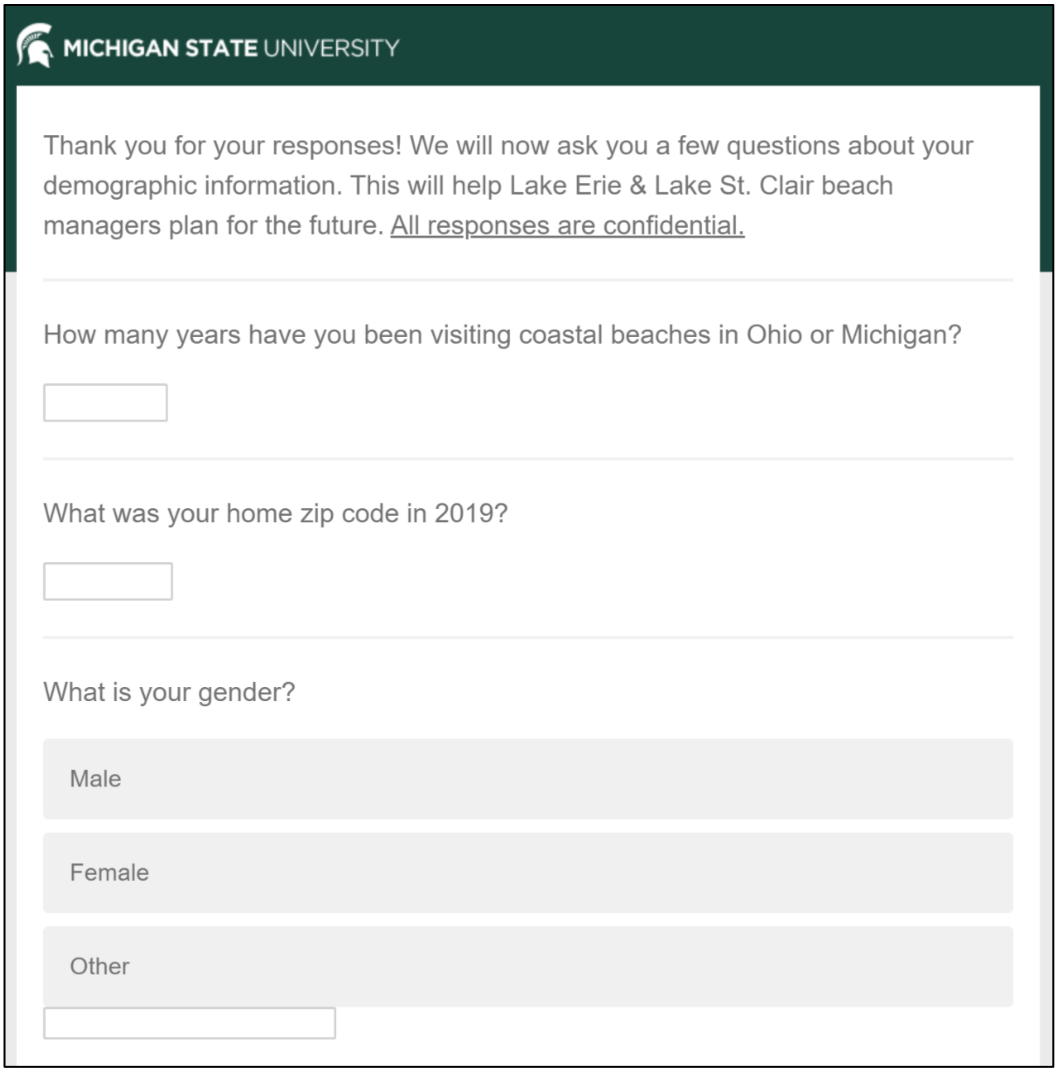
Thinking back on how you answered the questions about site visits and beach warnings and advisories, would you say that the current **coronavirus pandemic** and its effects made you more likely to avoid beaches with warnings or advisories, less likely to avoid beaches with warnings or advisories, or had no effect?

- **More** likely to avoid beaches with warnings and advisories
- **Less** likely to avoid beaches with warnings and advisories
- Had no effect

Suppose that the current social distancing policies and guidelines are lifted by the end of this May. Please indicate your agreement or disagreement with the following statements about how you expect the current coronavirus pandemic will affect your beach recreation in the summer of 2020.

	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree
I will be more likely to avoid all beaches	○	○	○	○	○
I will likely visit beaches as much or more than in the past	○	○	○	○	○
I will be more likely to go to different beaches than in the past	○	○	○	○	○
I will be less likely to avoid crowds at beaches	○	○	○	○	○
I will be more likely to avoid beaches with warnings and advisories	○	○	○	○	○

Figure B.1: (cont.d)


MICHIGAN STATE UNIVERSITY

Thank you for your responses! We will now ask you a few questions about your demographic information. This will help Lake Erie & Lake St. Clair beach managers plan for the future. All responses are confidential.

How many years have you been visiting coastal beaches in Ohio or Michigan?

What was your home zip code in 2019?

What is your gender?

Male

Female

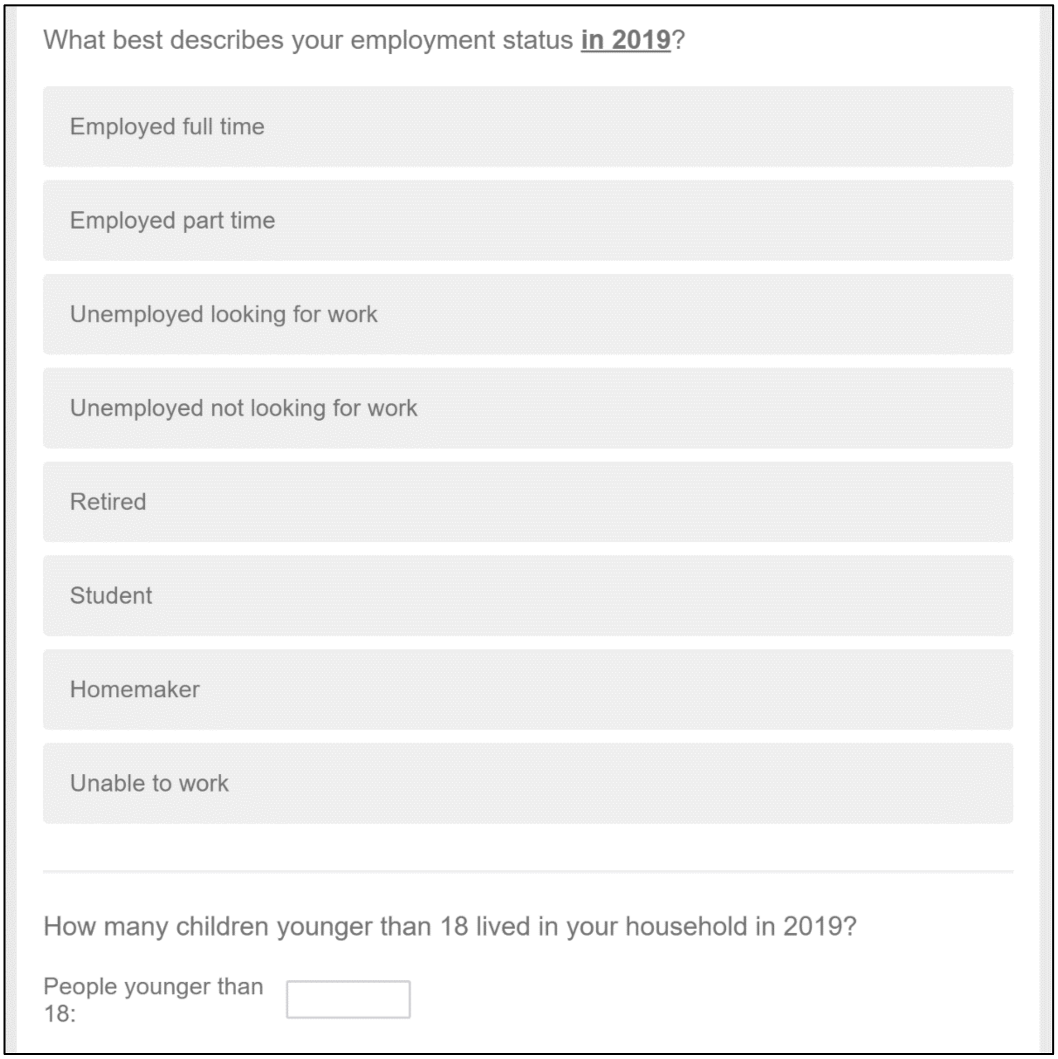
Other

Figure B.1: (cont.d)

What is the highest level or grade of school you had completed in 2019?

- Some high school or less
- High school graduate or GED
- Some college, no degree
- Two-year college (AA, AS) or technical degree
- Four-year college graduate (BA, BS)
- Some graduate work but did not receive a graduate degree
- Graduate degree (MA, MBA, PhD, JD, etc.)

Figure B.1: (cont.d)


What best describes your employment status **in 2019**?

- Employed full time
- Employed part time
- Unemployed looking for work
- Unemployed not looking for work
- Retired
- Student
- Homemaker
- Unable to work

How many children younger than 18 lived in your household in 2019?

People younger than 18:

Figure B.1: (cont.d)

What was your marital status in 2019?

- Married
- Single - Never Married
- Divorced
- Living with partner
- Other

Which of the following best describes your total household income before taxes **in 2019**?

- Less than $25,000 per year
- $25,000 to $49,999 per year
- $50,000 to $74,999 per year
- $75,000 to $99,999
- $100,000 to $149,999
- $150,000 to $199,999
- Over $200,000

Figure B.1: (cont.d)

Are you Spanish, Hispanic, or Latino or none of these?

Yes

None of these

Choose one or more races that you consider yourself to be:

White	Asian
Black or African American	Native Hawaiian or Pacific Islander
American Indian or Alaska Native	Other

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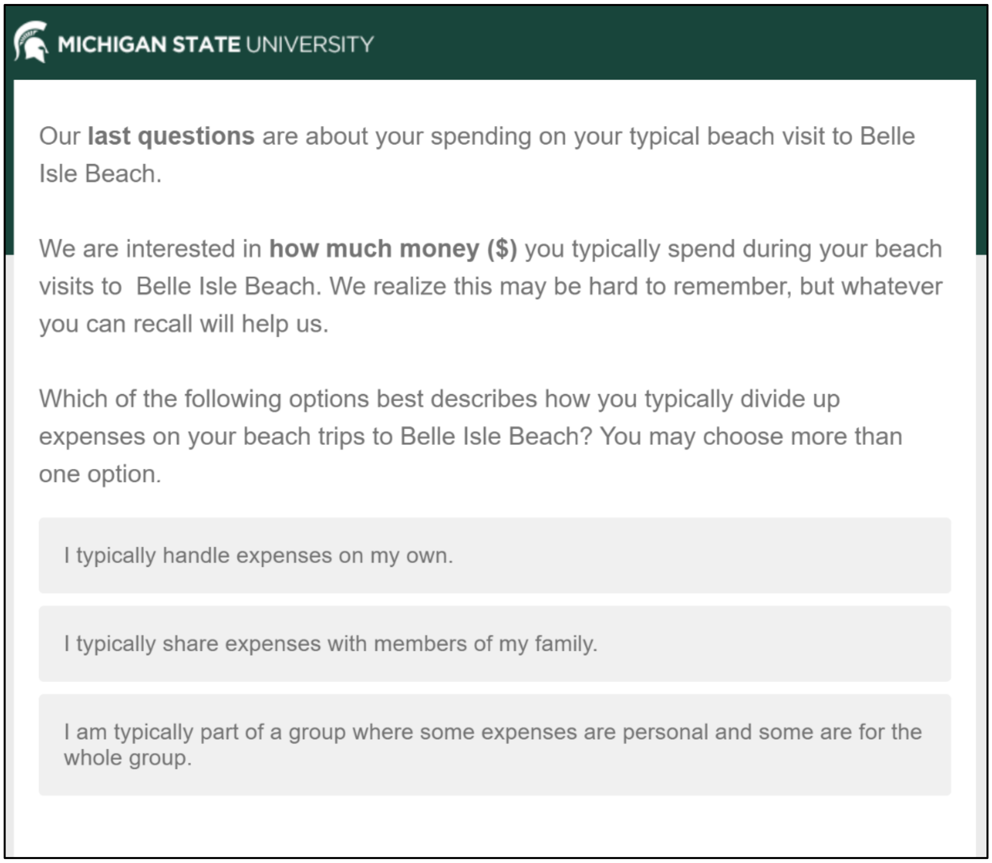
Please enter your personal expenses from your typical beach trip into the table below. If you can't remember exactly how much you usually spend, enter your best guess.

Final Question:

In the first column of the table, indicate how much money you spend within 10 miles of Belle Isle Beach during your typical trip to the beach. In the second column, indicate how much money you spend beyond 10 miles from Belle Isle Beach during your typical trip to the beach. If you don't spend any money on one or more of the categories, please enter "0".

Figure B.1: (cont.d)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Our **last questions** are about your spending on your typical beach visit to Belle Isle Beach.

We are interested in **how much money ($)** you typically spend during your beach visits to Belle Isle Beach. We realize this may be hard to remember, but whatever you can recall will help us.

Which of the following options best describes how you typically divide up expenses on your beach trips to Belle Isle Beach? You may choose more than one option.

- I typically handle expenses on my own.
- I typically share expenses with members of my family.
- I am typically part of a group where some expenses are personal and some are for the whole group.

Figure B.1: (cont.d)

Typical Trip Spending

	<u>Within</u> 10 miles of the beach	<u>Beyond</u> 10 miles from the beach
Restaurants		
Groceries (including drinks and snacks)		
Fuel (cars, trucks, boats, RVs etc)		
Rental Car Expenses		
Lodging (campground fees, motel and motel costs, etc.) *If you used reward points, enter expected monetary value.*		
Retail/Souvenir Shopping		
Other		

APPENDIX C: Data Collection

The intercept surveys were conducted on randomly selected beaches and days between May 27th and September 1st, with the exception of the 3 sites on Lake St. Clair and the Detroit River, where intercept surveys were conducted between June 29th and August 29th. For the 25 sites on the coast of Lake Erie, interviewer schedules were determined by a random sampling scheme, stratified by weekend (Saturday and Sunday) and weekday days. All weekend days were sampled, 4 of the 5 weekdays in any given week were sampled, and a random-number generator was used to determine the order of non-sampled weekdays. Each sampled day was then divided into two possible sampling shifts: a morning shifts from 10am to 4pm, and an afternoon shift from 1pm to 7pm. Two teams of interviewers were allocated to each sampled day and were randomly assigned to either both work the morning shift, both work the evening shift, or individually work both shifts. These 25 Lake Erie sites were then divided into 8 groups composed of 3 sites each (Group 1 had 4 sites), and each unique interviewer team/shift combination was randomly assigned one of these groups to determine which sites were sampled during each shift. Finally, the order in which the interviewers visited each site within the selected group was randomized, to avoid systematically visiting certain sites only at certain times of day.

The 3 beaches on Lake St. Clair and the Detroit River were sampled differently to accommodate less-frequent local interviewer availability. For these sites, three days were sampled per week in one of two arrangements: either both weekend days and one weekday were sampled, or one weekend day and two weekdays were sampled. The first week of sampling was randomly chosen to follow the two weekend-day/one weekday pattern, and each following week alternated between the day-sampling arrangements. Each day then was divided into a morning shift from 10am to 4pm and an afternoon shift from 2pm to 8pm. Only one interviewer team conducted interviews each day, and weekend shifts were selected using random number generation. Likewise, if a given week was selected to sample one weekday, the particular shift was randomly drawn from the ten possible shift-day combinations. If a given week was selected to sample two weekdays, the above process was completed to select the first day-shift combination, and then a sampled shift was randomly selected from the remaining eight shifts. Similar to the method used when sampling the 26 Lake Erie beaches, the order in which the interviewers visited the three sites was randomized for each shift.

APPENDIX D: Pilot Survey

In order to avoid using up respondent emails gathered in our initial intercept survey, we used Amazon's MTurk task completion web service to recruit Ohio residents, age 18 or older, to complete our pilot survey. In mid-April, we used MTurk to recruit Ohio residents via a short, five-minute Qualtrics screening survey concerning their visits to Lake Erie beaches in 2019. This first-stage survey was used to isolate Ohio residents who had actually visited one of the 28 beaches in our sample, before inviting them to take a second-stage survey which included the choice experiments questions. Accordingly, the first-stage survey was analogous to our summer 2019 intercept survey and allowed us to ensure that the pilot survey drew from a similar population of Ohio beach users.

The first-stage survey presented respondents with a list of the 28 beaches in our sample frame, and it asked respondents to indicate whether or not they were familiar with each beach. For each beach that a given respondent indicated he or she was familiar with, the respondent was asked how many times he or she visited the beach in 2019. Respondents were then asked to provide their zip code, gender, and indicate if they had a college degree. If a given respondent indicated that he or she was not familiar with any of the sites and/or visited none of the beaches in the sample during 2019, the survey ended. However, if a given respondent indicated that he or she had visited at least one of the 28 beaches during 2019, they were asked two questions about their typical 2019 beach trip. These included whether recreation was the primary purpose for the respondent's typical trip in 2019, and how many people typically ride in the same car with the respondent when driving to the beach. The demographic questions, as well as the questions about the respondents' typical trips, were analogous to questions posed to respondents during the initial intercept interviews. The first-stage screener was administered in two parts, hereby referred to as

1A and 1BC, to maximize the number of prospective respondents to invite to the second-stage survey. Out of 276 responses to the first-stage 1A instrument, 179 were eligible for the second-stage instrument. Out of 232 responses to the first-stage 1BC instrument, 161 were eligible for the second-stage instrument.

The second-stage pilot survey was designed to mirror the final follow-up survey sent to intercepted respondents from summer 2019. The survey began with a series of questions designed to educate respondents about harmful algal blooms and *E. coli* contamination in Lake Erie and Lake St. Clair. These questions also asked respondents about their experiences visiting area beaches, and about their attitudes concerning different beach attributes. Respondents were then asked to complete the five choice experiments and contingent behavior questions. The order in which these two sections were presented to respondents was randomized, to avoid any systematic ordering effects across the sample which could influence respondent answers to either section. Finally, respondents were asked a series of questions about their demographics, and their typical spending during beach trips.

The second-stage survey was distributed in three parts, hereby denoted instruments 2A, 2BC, and 2BC-Corona (this version included several questions related to the coronavirus pandemic, which will be discussed later). The five choice experiments in instrument 2A were designed in Ngene using our anecdotal prior assumptions concerning each attribute's marginal utility parameter and insights from the qualitative efforts.

The 179 respondents to instrument 1A who had visited at least one of the sampled beaches during 2019 were invited via MTurk to complete instrument 2A, and this resulted in 105 usable responses. Using these respondents' answers to the choice experiment questions, we ran a conditional logit choice model and used the estimated parameters from this model to generate a new D-efficient experimental design in Ngene. This design was subsequently used in instruments 2BC and 2BC-Corona. The remaining 74 eligible respondents to instrument 1A, as well as the 161 eligible respondents to instrument 1BC, were then invited to complete instrument 2BC, and this instrument resulted in 77 usable responses. At this stage, we designed instrument 2BC-Corona, which was identical to instruments 2A and 2BC but included the six additional coronavirus-related questions. These questions concerned whether respondents believed the Covid-19 pandemic influenced their answers, and whether they expected their future beach recreation behavior to change as a consequence of the pandemic. After making these changes, the remaining non-respondents from both instruments 1A and 1BC were invited to complete instrument 2BC-Corona, which resulted in 62 additional usable responses. In total, the final model used to generate the Ngene design for our follow-up survey used data from 176 respondents, and 880 unique choice situations.

Table D.1: Conditional Logit Estimates from Pilot Survey

Variables	(1)	(2) Neither Interactions	(3) Distance Interactions	(4) Model 1 WTD (in miles)
Mostly sand	0.888***	0.905***	0.898***	91
	(0.158)	(0.159)	(0.160)	
Half sand/half pebbles	0.303**	0.305**	0.301**	31
	(0.151)	(0.152)	(0.151)	
Clear water	0.852***	0.878***	0.871***	87
	(0.182)	(0.183)	(0.183)	
Somewhat murky water	0.440***	0.462***	0.459***	45
	(0.161)	(0.162)	(0.163)	
Never crowded	1.016***	1.035***	1.011***	104
	(0.169)	(0.167)	(0.168)	
Somewhat crowded	0.396***	0.404***	0.389***	40
	(0.148)	(0.149)	(0.149)	
Bac. warning in effect	-2.446***	-2.497***	-2.468***	-250
	(0.284)	(0.285)	(0.282)	
-Lifted 1 day ago	-1.307***	-1.331***	-1.316***	-134
	(0.216)	(0.217)	(0.214)	
-Lifted 3 days ago	-0.678***	-0.681***	-0.684***	-69
	(0.153)	(0.153)	(0.153)	
-Lifted 5 days ago	-0.755***	-0.756***	-0.760***	-77
	(0.149)	(0.148)	(0.150)	
HAB warning in effect	-2.208***	-2.239***	-2.214***	-226
	(0.332)	(0.329)	(0.332)	
-Lifted 1 day ago	-1.171***	-1.195***	-1.176***	-120
	(0.207)	(0.207)	(0.209)	
-Lifted 3 days ago	-0.809***	-0.813***	-0.806***	-83
	(0.150)	(0.150)	(0.151)	
-Lifted 5 days ago	-0.837***	-0.817***	-0.818***	-85
	(0.151)	(0.150)	(0.152)	
Neither	0.0967	1.008**	0.0902	
	(0.271)	(0.479)	(0.270)	
Distance	-0.00979***	-0.0102***	-0.0201***	
	(0.00268)	(0.00266)	(0.00619)	
nindist_neither	-0.00426**	-0.00409**	-0.00417**	
	(0.00189)	(0.00189)	(0.00187)	
neither_income		-1.17e-06		
		(2.26e-06)		
neither_white		-0.564		
		(0.351)		
neither_hispanic		-1.043**		
		(0.520)		
neither_male		-0.350		
		(0.236)		
neither_collgrad		-0.209		
		(0.237)		

Table D.1: (cont.)

dist_income			1.93e-09
			(3.04e-08)
dist_white			0.00786
			(0.00537)
dist_hispanic			0.00739
			(0.00596)
dist_male			0.00248
			(0.00336)
dist_collgrad			0.00233
			(0.00356)
Respondents	176	176	176
Choice Sets	880	880	880

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.2: Mixed Logit Estimates from Pilot Survey

Variables	(1) Parameter Estimate	(2) SD Estimates	(3) % with Parameter >0	(4) WTD at mean parameter est. (miles)
Mostly sand	8.237*** (2.834)	1.619*** (0.558)	100	118
Half sand/half pebbles	3.783** (1.698)	1.794** (0.826)	98	54
Clear water	4.862*** (1.643)	1.720** (0.840)	100	69
Somewhat murky water	1.282* (0.688)	7.921*** (2.291)	56	18
Never crowded	6.395*** (1.712)	5.913*** (1.611)	86	91
Somewhat crowded	4.966*** (1.258)	7.893*** (2.251)	74	71
Bac. warning in effect	-19.933*** (5.960)	16.863*** (4.683)	11	-285
-Lifted 1 day ago	-7.348*** (2.670)	10.191*** (2.988)	24	-105
-Lifted 3 days ago	-2.794** (1.157)	7.147*** (1.929)	35	-40
-Lifted 5 days ago	-3.342*** (1.120)	9.153*** (2.622)	36	-48
HAB warning in effect	-15.935*** (4.078)	14.078*** (3.414)	13	-228
-Lifted 1 day ago	-4.785*** (1.481)	9.067*** (2.613)	30	-68
-Lifted 3 days ago	-5.559*** (1.432)	10.789*** (3.087)	30	-79
-Lifted 5 days ago	-4.462*** (1.265)	12.706*** (3.881)	36	-64
Neither	4.713*** (1.779)	7.849*** (2.026)	73	
mindist_neither	-0.030*** (0.011)	0.489*** (0.149)	48	
Distance	-0.070** (0.030)			
Respondents	176	176	176	
Choice Sets	880	880	880	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.3: Contingent Behavior Response Percentages from Pilot Survey

CB Scenario	(1) I would have gone to the same beach.	(2) I would have gone to another beach.	(3) I would not have gone to any beach.
E. coli advisory- day of trip	8.52	35.23	56.25
HAB warning- day of trip	10.23	39.77	50
-Lifted 1 day before trip	23.3	39.77	36.93
-Lifted 3 days before trip	35.23	34.66	30.11
-Lifted 5 days before trip	56.82	26.7	16.48
HAB warning- next beach along the shore	32.95	28.41	38.64

Table D.4: COVID-19 Question Response Percentages from Pilot Survey

As a result of the coronavirus pandemic…	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**
I will be more likely to avoid all beaches.	22%	28%	14%	18%	18%
I will likely visit beaches as much or more than in the past.	21%	24%	20%	16%	19%
I will be more likely to go to different beaches than in the past.	20%	24%	24%	27%	5%
I will be less likely to avoid crowds at beaches	51%	10%	15%	14%	10%
I will be more likely to avoid beaches with warnings and advisories.	**2%**	**7%**	**25%**	**25%**	**41%**

APPENDIX E: Follow-up Disposition Tables and Item Non-response

Table E.1: Case Disposition Across Beach Sites Sampled in 2019

			Onsite Interviews*		Follow-Up Interviews		
Lake or River	County, State	Site	Completed	Emails	Invites	Partial Complete	Complete
Detroit River	Wayne, MI	Belle Isle Beach	366	262	259	10	113
Lake St. Clair	Macomb, MI	Lake St. Clair Metropark	164	113	113	5	31
		Walter & Mary Burke Park	88	63	62	5	22
Lake Erie	Monroe, MI	Sterling State Park	106	56	56	0	19
		Luna Pier Beach	38	19	19	2	6
	Lucas, OH	Maumee – Erie Beach	48	20	19	0	4
		Maumee – Inland Beach	20	11	11	0	5
	Ottawa, OH	Camp Perry Beach	19	9	9	1	4
		Port Clinton City Beach	30	17	17	1	6
		East Harbor State Park	120	56	54	2	24
	Erie, OH	Nickel Plate Beach	129	89	85	6	39
		Old Woman Creek Beach	41	24	24	2	16
		Sherod Park Beach	24	14	14	0	7
		Main Street Beach	178	118	118	7	42
		Showse Park Beach	10	6	6	0	2
	Lorain, OH	Lakeview Park Beach	193	115	115	0	48
		Century Park Beach	32	19	19	2	6
		Veteran’s Memorial Park Beach	29	17	16	1	7
	Cuyahoga, OH	Huntington Beach	256	161	158	8	88
		Edgewater Park Beach	445	295	289	12	109
		Euclid State Park	133	77	76	5	25
		Sims Beach	54	38	38	2	10
	Lake, OH	Headlands State Park	378	210	207	11	97
		Fairport Harbor	318	202	202	9	93
	Ashtabula, OH	Walnut Beach	305	176	172	10	78
		Geneva State Park	321	187	185	17	75
		Lakeshore Park Beach	80	50	49	4	20
		Conneaut Beach	310	152	147	4	71

*729 interviews were attempted at the 3 Detroit River and Lake St. Clair sites, and 4253 were attempted at the 25 Lake Erie sites.

Table E.2: Stated Preference Item Non-Response

Contingent Behavior Questions										
# of questions answered	0	1	2	3	4	5	6	7	8	9
% of respondents	7.69	0.66	0.28	0.56	0.37	0.37	3.56	1.31	3.84	81.35

Choice Experiments						
# of questions answered	0	1	2	3	4	5
% of respondents	1.78	1.87	0.84	0.84	3.09	91.57

Includes only respondents intercepted in 2019 who completed the follow-up survey,
i.e. provided an answer to at least one stated preference question (n = 1067).

APPENDIX F: Follow-Up Responses to Contingent Behavior & COVID-19 Questions

Table F.1: Contingent Behavior Response Percentages (2019 respondents)

CB Scenario	(1) I would have gone to the same beach.	(2) I would have gone to another beach.	(3) I would not have gone to any beach.	(4) N
E. coli advisory- day of trip	18.97	34.81	46.23	928
-Lifted 1 day before trip	34.55	31.95	33.51	961
-Lifted 3 days before trip	52.62	25.79	21.59	954
-Lifted 6 days before trip	76.22	11.42	12.36	963
HAB warning- day of trip	19.23	38.12	42.65	905
-Lifted 1 day before trip	39.03	30.02	30.95	966
-Lifted 3 days before trip	62.24	22.10	15.66	964
-Lifted 6 days before trip	80.10	11.03	8.87	970
HAB warning- next beach along the shore	56.29	15.18	28.52	922

Table F.2: COVID-19 Question Response Percentages (2019 Respondents)

As a result of the coronavirus pandemic…	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**N**
I will be more likely to avoid all beaches.	42.68	16.82	14.19	16.93	9.38	874
I will likely visit beaches as much or more than in the past.	16.57	17.15	20.02	19.79	26.47	869
I will be more likely to go to different beaches than in the past.	33.56	16.27	29.1	15.12	5.96	873
I will be less likely to avoid crowds at beaches	44.27	14.68	11.70	11.93	17.43	872
I will be more likely to avoid beaches with warnings and advisories.	**9.74**	**6.07**	**22.57**	**22.22**	**39.4**	**873**

APPENDIX G: Follow-Up Robustness Checks for Choice Experiment

Table G.1: Mixed Logit Robustness Checks

Variables	(1) All 2019 Respondents		(2) Under 29 mins. to complete (75th pctl.)		(3) Over 8 mins. to complete (10th pctl.)	
	Mean	SD	Mean	SD	Mean	SD
Distance	-0.0148***		-0.0145***		-0.0153***	
	(0.000721)		(0.000848)		(0.000770)	
Mostly sand	1.177***	0.680***	1.179***	0.559**	1.135***	0.614***
	(0.0892)	(0.120)	(0.107)	(0.250)	(0.0922)	(0.123)
Half sand/half pebbles	0.380***	0.0412	0.407***	0.463**	0.373***	0.0335
	(0.0734)	(0.145)	(0.0899)	(0.186)	(0.0794)	(0.159)
Clear water	1.500***	0.662***	1.419***	0.708***	1.520***	0.573***
	(0.103)	(0.158)	(0.122)	(0.209)	(0.102)	(0.197)
Somewhat murky water	0.707***	0.226***	0.628***	0.0359	0.747***	0.107
	(0.0738)	(0.0836)	(0.0870)	(0.251)	(0.0744)	(0.144)
Never crowded	1.011***	0.780***	0.892***	0.780***	1.041***	0.755***
	(0.0925)	(0.108)	(0.108)	(0.139)	(0.0943)	(0.103)
Somewhat crowded	0.643***	0.0873	0.550***	0.114	0.660***	0.00920
	(0.0780)	(0.0829)	(0.0888)	(0.116)	(0.0810)	(0.0912)
Bac. warning in effect	-3.938***	0.605	-3.792***	0.607	-4.056***	0.705
	(0.267)	(0.699)	(0.381)	(1.212)	(0.283)	(0.613)
-Lifted 1 day ago	-1.732***	0.554**	-1.679***	0.392	-1.746***	0.412
	(0.119)	(0.236)	(0.139)	(0.380)	(0.119)	(0.324)
-Lifted 3 days ago	-1.211***	0.180	-1.192***	0.328**	-1.177***	0.0239
	(0.0931)	(0.150)	(0.108)	(0.153)	(0.0908)	(0.323)
-Lifted 6 days ago	-1.136***	0.00744	-1.192***	0.187	-1.137***	0.219
	(0.0900)	(0.165)	(0.105)	(0.203)	(0.0953)	(0.299)
HAB warning in effect	-3.855***	1.971***	-3.501***	1.783***	-3.813***	1.788***
	(0.314)	(0.475)	(0.312)	(0.481)	(0.261)	(0.379)
-Lifted 1 day ago	-1.280***	0.200	-1.158***	0.169	-1.245***	0.0204
	(0.102)	(0.149)	(0.115)	(0.267)	(0.104)	(0.195)
-Lifted 3 days ago	-0.873***	0.332**	-0.812***	0.315	-0.899***	0.227
	(0.0870)	(0.166)	(0.100)	(0.235)	(0.0902)	(0.255)
-Lifted 6 days ago	-0.454***	0.214	-0.490***	0.293	-0.441***	0.0543
	(0.0780)	(0.173)	(0.0922)	(0.199)	(0.0822)	(0.172)
Neither	-0.554***	1.657***	-0.691***	1.659***	-0.568***	1.707***
	(0.127)	(0.0881)	(0.144)	(0.112)	(0.134)	(0.0875)
Respondents	1048		779		944	
Choice Occasions	5082		3775		4640	
Correlation with model 1 means			0.9988		0.9997	

Table G.1: (cont.)

Variables	(1) All 2019 Respondents		(4) Respondents who live within 50 miles of a beach (75th pctl.)		(5) Only respondents with transitive preferences	
	Mean	SD	Mean	SD	Mean	SD
Distance	-0.0148***		-0.0161***		-0.0151***	
	(0.000721)		(0.000844)		(0.000819)	
Mostly sand	1.177***	0.680***	1.084***	0.722***	1.198***	0.697***
	(0.0892)	(0.120)	(0.104)	(0.158)	(0.0941)	(0.132)
Half sand/half pebbles	0.380***	0.0412	0.350***	0.166	0.376***	0.160
	(0.0734)	(0.145)	(0.0881)	(0.319)	(0.0796)	(0.186)
Clear water	1.500***	0.662***	1.425***	0.734***	1.493***	0.798***
	(0.103)	(0.158)	(0.116)	(0.171)	(0.107)	(0.151)
Somewhat murky water	0.707***	0.226***	0.653***	0.0100	0.724***	0.0876
	(0.0738)	(0.0836)	(0.0850)	(0.156)	(0.0775)	(0.132)
Never crowded	1.011***	0.780***	0.863***	0.774***	0.986***	0.708***
	(0.0925)	(0.108)	(0.108)	(0.116)	(0.0992)	(0.121)
Somewhat crowded	0.643***	0.0873	0.482***	0.165	0.612***	0.0343
	(0.0780)	(0.0829)	(0.0906)	(0.120)	(0.0843)	(0.0933)
Bac. warning in effect	-3.938***	0.605	-4.323***	1.840***	-4.045***	1.002*
	(0.267)	(0.699)	(0.456)	(0.616)	(0.318)	(0.583)
-Lifted 1 day ago	-1.732***	0.554**	-1.675***	0.182	-1.716***	0.497**
	(0.119)	(0.236)	(0.132)	(0.467)	(0.126)	(0.244)
-Lifted 3 days ago	-1.211***	0.180	-1.299***	0.144	-1.199***	0.180
	(0.0931)	(0.150)	(0.117)	(0.494)	(0.0977)	(0.149)
-Lifted 6 days ago	-1.136***	0.00744	-1.185***	0.106	-1.155***	0.395*
	(0.0900)	(0.165)	(0.106)	(0.162)	(0.0982)	(0.225)
HAB warning in effect	-3.855***	1.971***	-3.596***	2.135***	-3.829***	1.976***
	(0.314)	(0.475)	(0.335)	(0.507)	(0.291)	(0.414)
-Lifted 1 day ago	-1.280***	0.200	-1.238***	0.104	-1.257***	0.223
	(0.102)	(0.149)	(0.119)	(0.224)	(0.119)	(0.255)
-Lifted 3 days ago	-0.873***	0.332**	-0.870***	0.327*	-0.849***	0.302*
	(0.0870)	(0.166)	(0.100)	(0.181)	(0.0941)	(0.182)
-Lifted 6 days ago	-0.454***	0.214	-0.363***	0.0446	-0.469***	0.240
	(0.0780)	(0.173)	(0.0907)	(0.149)	(0.0859)	(0.146)
Neither	-0.554***	1.657***	-0.704***	1.515***	-1.109***	1.753***
	(0.127)	(0.0881)	(0.143)	(0.0961)	(0.144)	(0.0967)
Respondents	1048		801		1016	
Choice Occasions	5082		3881		4465	
Correlation with model 1 means			0.9963		0.9962	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table G.2: Ordering Effects in Mixed Logit Model

Variables	(2) CB|CE - contingent behavior appeared first			(3) CE|CB – choice experiment appeared first		
	Mean	SD	WTD (miles)	Mean	SD	WTD (miles)
Distance	-0.0151***			-0.0149***		
	(0.00104)			(0.00101)		
Mostly sand	1.205***	0.521*	80	1.172***	0.742***	79
	(0.127)	(0.288)		(0.127)	(0.169)	
Half sand/half pebbles	0.476***	0.157	32	0.316***	0.458	21
	(0.104)	(0.225)		(0.118)	(0.293)	
Clear water	1.316***	0.568***	87	1.703***	0.685**	114
	(0.141)	(0.213)		(0.145)	(0.288)	
Somewhat murky water	0.732***	0.0858	48	0.684***	0.408**	46
	(0.105)	(0.187)		(0.105)	(0.177)	
Never crowded	0.807***	0.832***	53	1.150***	0.710***	77
	(0.130)	(0.116)		(0.132)	(0.174)	
Somewhat crowded	0.583***	-0.0790	39	0.635***	0.0859	43
	(0.115)	(0.161)		(0.109)	(0.166)	
Bac. warning in effect	-3.820***	1.100*	-253	-4.480***	1.306*	-301
	(0.415)	(0.582)		(0.435)	(0.697)	
-Lifted 1 day ago	-1.608***	0.442	-106	-1.874***	0.574	-126
	(0.165)	(0.384)		(0.173)	(0.449)	
-Lifted 3 days ago	-1.107***	0.218	-73	-1.263***	0.0224	-85
	(0.131)	(0.203)		(0.133)	(0.285)	
-Lifted 6 days ago	-0.924***	0.308	-61	-1.331***	0.0763	-89
	(0.125)	(0.354)		(0.131)	(0.197)	
HAB warning in effect	-3.540***	1.360**	-234	-3.677***	1.568	-247
	(0.384)	(0.652)		(0.489)	(1.018)	
-Lifted 1 day ago	-1.163***	0.00477	-77	-1.409***	0.136	-95
	(0.148)	(0.306)		(0.144)	(0.234)	
-Lifted 3 days ago	-0.889***	0.0804	-59	-0.855***	0.00345	-57
	(0.126)	(0.664)		(0.122)	(0.347)	
-Lifted 6 days ago	-0.428***	0.231	-28	-0.543***	0.506***	-36
	(0.114)	(0.154)		(0.114)	(0.178)	
Neither	-0.612***	1.817***		-0.572***	1.581***	
	(0.185)	(0.133)		(0.189)	(0.121)	
Respondents		508			540	
Choice Occasions		2483			2599	
Correlation with Model 1 means		0.9983			0.9963	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table G.3: Ordering Effects in Contingent Behavior Response Percentages

CB Scenario	(1) I would have gone to the same beach.		(2) I would have gone to another beach.		(3) I would not have gone to any beach.	
	CE|CB	CB|CE	CE|CB	CB|CE	CE|CB	CB|CE
E. coli advisory- day of trip	18.14	19.75	39.38	30.46	42.48	49.79
-Lifted 1 day before trip	37.42	31.85	33.33	30.65	29.25	37.50
-Lifted 3 days before trip	60.00	45.75	24.35	27.13	15.65	27.13
-Lifted 6 days before trip	82.19	70.62	9.87	12.88	7.94	16.50
HAB warning- day of trip	16.97	21.38	43.44	33.05	39.59	45.57
-Lifted 1 day before trip	42.92	35.40	29.61	30.40	27.47	34.20
-Lifted 3 days before trip	68.25	56.69	20.73	23.35	11.02	19.96
-Lifted 6 days before trip	85.26	75.30	8.97	12.95	5.77	11.75
HAB warning- next beach along the shore	61.61	51.27	13.39	16.88	25.00	31.86
Comparison with pooled data results from Table IVa						
Average difference	-3.72	3.47	-0.29	0.30	4.02	-3.77
Min absolute difference	0.83	0.78	0.41	0.38	3.06	2.88
Max absolute difference	7.38	6.87	5.32	5.07	5.94	5.54
Correlation	0.9996	0.9963	0.9926	0.9835	0.9979	0.9980

Table G.4: Choice Model Estimate Comparisons

Variables	(1) Mixed Logit			(3) Conditional Logit			(4) Nested Logit		
	Mean Estimate	SD Estimates	WTD (miles)	Estimate	WTD	% diff. from m. logit WTD	Estimate	WTD	% diff. from m. logit WTD
Distance	-0.0148***			-0.0112***			-0.00941***		
	(0.000721)			(0.000501)			(0.000638)		
Mostly sand	1.177***	0.680***	80	0.834***	74	-7%	0.758***	81	1%
	(0.0892)	(0.120)		(0.0674)			(0.0624)		
Half sand/half pebbles	0.380***	0.0412	26	0.297***	26	3%	0.273***	29	13%
	(0.0734)	(0.145)		(0.0584)			(0.0472)		
Clear water	1.500***	0.662***	101	1.053***	94	-8%	0.911***	97	-5%
	(0.103)	(0.158)		(0.0727)			(0.0756)		
Somewhat murky water	0.707***	0.226***	48	0.524***	47	-2%	0.441***	47	-2%
	(0.0738)	(0.0836)		(0.0560)			(0.0537)		
Never crowded	1.011***	0.780***	68	0.725***	65	-6%	0.681***	72	6%
	(0.0925)	(0.108)		(0.0706)			(0.0612)		
Somewhat crowded	0.643***	0.0873	43	0.501***	45	3%	0.439***	47	7%
	(0.0780)	(0.0829)		(0.0621)			(0.0546)		
Bac. warning in effect	-3.938***	0.605	-266	-2.733***	-243	-9%	-2.427***	-258	-3%
	(0.267)	(0.699)		(0.145)			(0.164)		
-Lifted 1 day ago	-1.732***	0.554**	-117	-1.195***	-106	-9%	-1.095***	-116	-1%
	(0.119)	(0.236)		(0.0805)			(0.0803)		
-Lifted 3 days ago	-1.211***	0.180	-82	-0.801***	-71	-13%	-0.709***	-75	-8%
	(0.0931)	(0.150)		(0.0673)			(0.0640)		
-Lifted 6 days ago	-1.136***	0.00744	-77	-0.756***	-67	-12%	-0.653***	-69	-10%
	(0.0900)	(0.165)		(0.0683)			(0.0639)		
HAB warning in effect	-3.855***	1.971***	-261	-2.256***	-201	-23%	-2.022***	-215	-18%
	(0.314)	(0.475)		(0.133)			(0.143)		
-Lifted 1 day ago	-1.280***	0.200	-87	-0.942***	-84	-3%	-0.789***	-84	-3%
	(0.102)	(0.149)		(0.0754)			(0.0798)		
-Lifted 3 days ago	-0.873***	0.332**	-59	-0.646***	-57	-3%	-0.549***	-58	-1%
	(0.0870)	(0.166)		(0.0656)			(0.0614)		
-Lifted 6 days ago	-0.454***	0.214	-31	-0.294***	-26	-15%	-0.276***	-29	-4%
	(0.0780)	(0.173)		(0.0595)			(0.0498)		
Neither (nest in n. logit)	-0.554***	1.657***		-0.240**			-0.302***		
	(0.127)	(0.0881)		(0.0960)			(0.0816)		
Nesting parameter							0.759***		
							0.062		
Respondents		1048			1048			1048	
Choice Occasions		5082			5082			5082	
Corr. w/ Model 1 means					.996			.999	

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

APPENDIX H: 2019 Respondent Summary Statistics

Table H.1: 2019 Respondent Summary Statistics

Variable	Mean			Min	Max	N		
	(1)	(2)	(3)			(1)	(2)	(3)
Male (0/1)*	.	.	0.24	0	1	.	.	964
Hispanic (0/1)*	.	.	0.03	0	1	.	.	853
White (0/1)*	.	.	0.94	0	1	.	.	847
Income (in thousands)*	.	.	80.9	12.5	250	.	.	854
Age	42.9	41.1	42	22	70	4159	2535	1195
College graduate (0/1)	0.58	0.62	0.58	0	1	4140	2524	959
Have you, or do you plan to, enter the water? (0/1)	0.69	0.73	0.73	0	1	4157	2534	1196
Is rec. the primary purpose of visit? (0/1)	0.95	0.95	0.95	0	1	4163	2538	1196

(1) Intercept survey participants
(2) Intercept participants who provided an email
(3) Follow-up respondents used in analysis
*These variables are only available for follow-up respondents

APPENDIX I: Mixed Logit Conditional Parameter Regressions

Table I.1: Summary of Mixed Logit Posterior Parameter Regressions

Conditional Beta for Dependent Variable	R^2	Adjusted R^2	P-value for regression F test	Number of demographic regressors significant at 5%	Demographic regressors significant at 5%	Number of demographic regressors significant at 1%	Demographic regressors significant at 1%
Mostly sand	0.008	0.005	0.86	0		0	
Half sand/half pebbles	0.021	0.009	0.055	0		1	Employed full time (0/1)
Clear water	0.009	0.003	0.74	0		0	
Somewhat murky water	0.017	0.005	0.16	1	Male (0/1)	0	
Never crowded	0.017	0.005	0.17	1	College grad (0/1)	1	Visits to intercepted beach each season
Somewhat crowded	0.007	0.005	0.87	0		0	
Bac. warning in effect	0.014	0.001	0.35	1	Years visit area beaches	0	
-Lifted 1 day ago	0.016	0.003	0.22	1	Visits to intercepted beach each season	0	
-Lifted 3 days ago	0.012	0.0004	0.48	0		0	
-Lifted 6 days ago	0.018	0.005	0.14	0		0	
HAB warning in effect	0.017	0.004	0.18	2	College grad (0/1) & Num. children in hh.	0	
-Lifted 1 day ago	0.014	0.002	0.32	1	White (0/1)	0	
-Lifted 3 days ago	0.015	0.003	0.24	0		1	Years visit area beaches
-Lifted 6 days ago	0.024	0.011	0.025	1	College grad (0/1)	1	Enter water during intercepted trip? (0/1)
Average	0.015	0.004		0.57		0.29	

APPENDIX J: Choice Experiment Simulation Results

Table J.1: Choice Experiment Simulation Results

Scenario	(1) Avg. % change in prob. of visiting same site	(2) Implied percentage of CE respondents who would go to same site	(3) Percentage of CB respondents who would go to the same site	Δ
Bac. warning in effect	-94%	6%	19%	-13%
-Lifted 1 day ago	-60%	40%	39%	-1%
-Lifted 3 days ago	-44%	56%	62%	6%
-Lifted 6 days ago	-41%	59%	80%	21%
HAB warning in effect	-93%	7%	19%	12%
-Lifted 1 day ago	-46%	54%	35%	-19%
-Lifted 3 days ago	-32%	68%	53%	-15%
-Lifted 6 days ago	-17%	83%	76%	-17%
Correlation between (2) and (3)			0.85	

APPENDIX K: Creation of Trip Estimates from Individual Weights

Once the individual weight w_{hijk} is obtained for every intercepted beachgoer, these weights are summed over the K_h beachgoers in a given stratum h to recover an estimate of the total visitation in each stratum:

$$\widehat{T_h} = \sum_{k=1}^{K_h} w_{hijk}$$

Total estimated visits to the 3 sites where Michigan State interviewers conducted interviews is computed by summing $\widehat{T_h}$ over the 4 MSU-specific strata, and the same strategy is used for the 25 sites in the 6 OSU-specific strata:

$$\widehat{T_{MSU,JUL/AUG}} = \sum_{h=1}^{4} \widehat{T_h}$$

$$\widehat{T_{OSU}} = \sum_{h=5}^{10} \widehat{T_h}$$

Because the Michigan State interviewer team did not conduct interviews from May 27th to June 28th, at this stage we are only able to construct $\widehat{T_{MSU,JUL/AUG}}$, which estimates site visitation from June 29th to September 1st at Belle Isle, St. Clair Metropark, and Burke Park. Conversely, the Ohio State team conducted interviews from May 27th to September 1st, and so $\widehat{T_{OSU}}$ estimates visitation across the full summer season at the 25 Erie sites. In order to estimate full seasonal visitation to all 28 sites in our sample, we needed to recover estimated visitation to the 3 MSU sites during the period of May 27th to June 28th. Accordingly, we first partition estimated visits to OSU-sampled sites into two mutually exclusive groups based on the sampling date:

$$\widehat{T_{OSU,JUL/AUG}} = \sum_{h=6,7,9,10} \widehat{T_h}$$

$$\widehat{T_{OSU,MAY/JUN}} = \sum_{h=5,8} \widehat{T_h}$$

We then compute σ, the ratio of total estimated visits to OSU-sampled sites to the number of estimated visits to OSU-sampled sites in July and August.

$$\widehat{T_{OSU}} / \widehat{T_{OSU,JUL/AUG}} = \sigma > 1$$

Note that multiplying $\widehat{T_{OSU,JUL/AUG}}$ by σ returns the total estimated seasonal trips for the OSU-sampled sites. To adjust for the lack of data on May and June trips to MSU-sampled sites, we first assume that the constant σ also characterizes the relationship between the known $\widehat{T_{MSU,JUL/AUG}}$ and the unknown $\widehat{T_{MSU}}$:

$$\widehat{T_{MSU}} / \widehat{T_{MSU,JUL/AUG}} = \sigma > 1$$

Operating under this assumption, we inflate each individual weight w_{hijk} assigned to a beachgoer in the MSU-specific strata by σ and sum these weights to recover $\widehat{T_{MSU}}$:

$$\sum_{h=1}^{4} \sum_{k=1}^{K_h} \sigma(w_{hijk}) = \sigma \sum_{h=1}^{4} \widehat{T_h} = \sigma \widehat{T_{MSU,JUL/AUG}} = \widehat{T_{MSU}}$$

Table K.1: Strata Used in Visitation Estimation

Stratum	Interviewer Team	Time Period	Day Period	# Intercepted Trips
1	MSU	June 29- August 1	Weekday	83
2	MSU	August 1 – September 1	Weekday	134
3	MSU	June 29- August 1	Weekend	289
4	MSU	August 1 – September 1	Weekend	103
5	OSU	May 27 – July 1	Weekday	638
6	OSU	July 1 – August 1	Weekday	766
7	OSU	August 1 – September 1	Weekday	632
8	OSU	May 27 – July 1	Weekend	320
9	OSU	July 1 – August 1	Weekend	650
10	OSU	August 1 – September 1	Weekend	544

APPENDIX L: Observed HAB and Bacterial Warnings in 2019 Season

Table L.1: Observed HAB and Bacterial Warnings in 2019 Season

Warning type	Affected site	Number of warnings during 2019 season	Number of affected days	Number of days 1-2 days after warning	Number of days 3-5 days after warning	Number of days 6 days after warning
Bacterial	Camp Perry Beach	3	22	6	9	3
	Century Park Beach	13	56	14	11	3
	Conneaut Beach	1	3	2	1	0
	East Harbor State Park	3	9	6	7	2
	Fairport Harbor Park Beach	1	3	2	3	1
	Geneva State Park	2	6	4	6	2
	Headlands Beach St. Park	1	3	2	3	1
	Lakeshore Park Beach	2	6	4	6	2
	Lakeview Park Beach	12	45	14	17	5
	Main Street Beach	13	47	14	18	6
	Maumee – Inland Beach	9	74	8	7	2
	Nickel Plate Beach	4	15	6	9	3
	Old Woman Creek Beach	4	13	8	12	4
	Sims Park Beach	5	32	10	11	3
	Sherod Park Beach	12	46	13	11	6
	Showse Park Beach	10	37	13	16	5
	Veteran’s Beach	15	58	18	20	6
HAB	Edgewater Park Beach	1	9	2	3	1
	Euclid State Park	1	9	2	3	1
	Huntington Beach	1	10	2	3	1
	Maumee- Erie Beach	2	45	2	3	1
Total		115	548	152	179	58
Mean		5.48	26.1	7.24	8.52	2.76
Max		15	74	18	20	6
Min		1	3	2	1	0

APPENDIX M: Re-calibrated Baseline ASC Adjustments and Welfare Estimates

Table M.1: Recalibrated ASC Estimates and Adjustments for All Sites and Scenarios (* denotes unaffected site/ no ASC adjustment)

Site	Baseline ASC	HAB warning	HAB 1 day ago	HAB 3 days ago	HAB 6 days ago	HAB next beach	Bac. warning	Bac. 1 day ago	Bac. 3 days ago	Bac. 6 days ago
Belle Isle*	**-6.126**	-0.235	-0.147	-0.072	-0.036	-0.086	-0.241	-0.159	-0.084	-0.040
Walter & Mary Burke Park*	**-6.268**	-0.215	-0.130	-0.061	-0.031	-0.074	-0.221	-0.142	-0.073	-0.033
Luna Pier Beach*	**-6.274**	-0.195	-0.115	-0.052	-0.026	-0.064	-0.200	-0.126	-0.062	-0.028
Lake St. Clair Metropark*	**-6.228**	-0.216	-0.131	-0.062	-0.031	-0.075	-0.222	-0.143	-0.074	-0.034
Sterling State Park*	**-6.106**	-0.218	-0.133	-0.063	-0.031	-0.076	-0.224	-0.145	-0.075	-0.034
Camp Perry Beach	**-6.128**	-0.194	-0.114	-0.052	-0.026	-0.064	-0.200	-0.125	-0.062	-0.028
Century Park Beach	**-6.131**	-0.193	-0.113	-0.052	-0.025	-0.063	-0.199	-0.124	-0.062	-0.028
Conneaut Beach	**-5.929**	-0.221	-0.135	-0.064	-0.032	-0.077	-0.227	-0.147	-0.076	-0.035
East Harbor State Park	**-5.9**	-0.210	-0.126	-0.059	-0.029	-0.072	-0.216	-0.138	-0.070	-0.032
Edgewater Park Beach	**-5.913**	-0.220	-0.135	-0.064	-0.032	-0.077	-0.226	-0.147	-0.076	-0.035
Euclid State Park	**-6.152**	-0.193	-0.114	-0.052	-0.025	-0.063	-0.199	-0.125	-0.062	-0.028
Fairport Harbor Beach	**-5.939**	-0.202	-0.120	-0.056	-0.028	-0.068	-0.208	-0.132	-0.066	-0.030

Table M.1: (cont.)

Geneva State Park	**-5.902**	-0.204	-0.122	-0.057	-0.028	-0.069	-0.209	-0.133	-0.067	-0.031
Headlands Beach State Park	**-5.94**	-0.204	-0.122	-0.057	-0.028	-0.069	-0.210	-0.134	-0.067	-0.031
Huntington Beach	**-6.013**	-0.200	-0.119	-0.055	-0.027	-0.066	-0.205	-0.130	-0.065	-0.030
Lakeshore Park Beach	**-6.09**	-0.196	-0.115	-0.053	-0.026	-0.064	-0.201	-0.126	-0.063	-0.028
Lakeview Park Beach	**-5.939**	-0.204	-0.122	-0.056	-0.028	-0.068	-0.209	-0.133	-0.067	-0.031
Main Street Beach	**-5.977**	-0.201	-0.119	-0.055	-0.027	-0.067	-0.206	-0.131	-0.066	-0.030
Maumee Bay State Park- Erie	**-6.041**	-0.210	-0.127	-0.059	-0.030	-0.072	-0.216	-0.138	-0.071	-0.032
Maumee Bay State Park- Inland	**-6.08**	-0.204	-0.122	-0.057	-0.028	-0.069	-0.209	-0.133	-0.067	-0.031
Nickel Plate Beach	**-6.01**	-0.199	-0.118	-0.054	-0.027	-0.066	-0.205	-0.129	-0.065	-0.029
Old Woman Creek Beach	**-6.248**	-0.192	-0.113	-0.051	-0.025	-0.062	-0.198	-0.124	-0.061	-0.028
Port Clinton City Beach*	**-6.175**	-0.193	-0.113	-0.052	-0.025	-0.063	-0.199	-0.125	-0.062	-0.028
Sims Park Beach	**-6.174**	-0.193	-0.113	-0.052	-0.025	-0.063	-0.198	-0.124	-0.062	-0.028
Sherod Park Beach	**-6.205**	-0.192	-0.113	-0.051	-0.025	-0.063	-0.198	-0.124	-0.061	-0.028
Showse Park Beach	**-6.316**	-0.191	-0.112	-0.051	-0.025	-0.062	-0.197	-0.123	-0.061	-0.027
Veteran’s Beach	**-6.127**	-0.194	-0.114	-0.052	-0.025	-0.063	-0.199	-0.125	-0.062	-0.028
Walnut Beach*	**-5.945**	-0.207	-0.125	-0.058	-0.029	-0.071	-0.213	-0.136	-0.069	-0.032

Table M.2: Recalibrated Value per Lost Trip Estimates for All Sites and Scenarios (* denotes unaffected site)

Site	HAB warning	HAB 1 day ago	HAB 3 days ago	HAB 6 days ago	HAB next beach	Bac. warning	Bac. 1 day ago	Bac. 3 days ago	Bac. 6 days ago
Belle Isle*	$19.85	$20.70	$21.88	$22.60	$21.62	$19.81	$20.55	$21.65	$22.52
Walter & Mary Burke Park*	$17.64	$18.00	$18.48	$18.76	$18.37	$17.63	$17.94	$18.38	$18.73
Luna Pier Beach*	$15.60	$15.65	$15.73	$15.78	$15.71	$15.59	$15.64	$15.71	$15.77
Lake St. Clair Metropark*	$17.76	$18.17	$18.75	$19.11	$18.62	$17.74	$18.09	$18.64	$19.07
Sterling State Park*	$17.95	$18.39	$18.99	$19.37	$18.86	$17.93	$18.31	$18.87	$19.33
Camp Perry Beach	$15.55	$15.60	$15.66	$15.71	$15.65	$15.55	$15.59	$15.65	$15.71
Century Park Beach	$15.45	$15.48	$15.53	$15.56	$15.52	$15.45	$15.48	$15.52	$15.56
Conneaut Beach	$18.22	$18.68	$19.28	$19.64	$19.15	$18.20	$18.59	$19.16	$19.60
East Harbor State Park	$17.10	$17.38	$17.77	$18.01	$17.68	$17.09	$17.33	$17.69	$17.98
Edgewater Park Beach	$18.20	$18.69	$19.39	$19.82	$19.23	$18.17	$18.60	$19.25	$19.77
Euclid State Park	$15.47	$15.50	$15.55	$15.59	$15.54	$15.47	$15.50	$15.54	$15.58
Fairport Harbor Park Beach	$16.34	$16.51	$16.76	$16.93	$16.70	$16.34	$16.48	$16.71	$16.91
Geneva State Park	$16.50	$16.69	$16.98	$17.17	$16.92	$16.49	$16.66	$16.92	$17.15

Table M.2: (cont.)

Headlands Beach State Park	$16.56	$16.75	$17.03	$17.21	$16.97	$16.55	$16.72	$16.98	$17.19
Huntington Beach	$16.10	$16.23	$16.42	$16.55	$16.38	$16.10	$16.21	$16.38	$16.54
Lakeshore Park Beach	$15.69	$15.76	$15.86	$15.93	$15.83	$15.69	$15.74	$15.84	$15.92
Lakeview Park Beach	$16.48	$16.67	$16.95	$17.12	$16.88	$16.48	$16.64	$16.89	$17.11
Main Street Beach	$16.21	$16.35	$16.57	$16.71	$16.52	$16.20	$16.32	$16.52	$16.70
Maumee Bay State Park- Erie	$17.15	$17.45	$17.89	$18.17	$17.79	$17.14	$17.40	$17.80	$18.14
Maumee Bay State Park- Inland	$16.50	$16.69	$16.98	$17.17	$16.92	$16.49	$16.66	$16.92	$17.15
Nickel Plate Beach	$16.05	$16.16	$16.34	$16.46	$16.30	$16.04	$16.14	$16.30	$16.45
Old Woman Creek Beach	$15.35	$15.36	$15.38	$15.40	$15.38	$15.35	$15.36	$15.38	$15.39
Port Clinton City Beach*	$15.46	$15.49	$15.53	$15.56	$15.52	$15.46	$15.48	$15.52	$15.56
Sims Park Beach	$15.43	$15.46	$15.49	$15.52	$15.49	$15.43	$15.45	$15.49	$15.52
Sherod Park Beach	$15.36	$15.38	$15.40	$15.42	$15.40	$15.36	$15.37	$15.40	$15.42
Showse Park Beach	$15.29	$15.30	$15.31	$15.31	$15.30	$15.29	$15.30	$15.31	$15.31
Veteran’s Beach	$15.49	$15.53	$15.58	$15.62	$15.57	$15.49	$15.52	$15.57	$15.61
Walnut Beach*	$16.87	$17.13	$17.52	$17.78	$17.43	$16.86	$17.08	$17.44	$17.75

APPENDIX N: Contraction Mapping Substitution Predictions

The contraction mapping algorithm calibrates a change in the ASCs so that the site choice model generates the same pattern of demand implied by the contingent behavior responses. This pattern of demand depends on the proportion of respondents who indicated that they would visit the same site given each HAB or bacterial scenario. However, respondents could also select that they would have gone to another beach or stayed home. The proportions of agents in the recalibrated demand model that select each of these two options are dictated by the estimated site choice model structure, rather than the pattern of demand reported in the CB responses. Table XIV compares the responses from the follow-up survey with the predictions from our nested logit model. In the case of the percentage of respondents who selected that they would go to the same beach, our model's predictions are very close to the stated preference data. However, our model predicts that the majority of respondents who elect to not go to the same site would substitute to other sites, rather than stay home. Indeed, for each contingent behavior scenario, under 1 percent of beachgoers are predicted to stay at home. In comparison, the stated preference results indicate that a fairly large percentage of respondents would stay home for each scenario (26.7% on average). A similar pattern of visitation predictions was observed by Tanner et al. (2019), who estimated a similar calibrated RP-SP model of southern California forest recreation. Taken together, these results provide evidence that models like the one used in this paper are useful in terms of estimating the welfare effects of environmental quality changes but may not as be accurate in forecasting patterns of site substitution.

Table N.1: Comparison of Contingent Behavior Data and Nested Logit Predictions

CB Scenario	Survey Responses: I would have gone to the same beach.	Survey Responses: I would have gone to another beach.	Survey Responses: I would not have gone to any beach.	Model Predictions, weighted by predicted trips: I would have gone to the same beach.	Model Predictions, weighted by predicted trips: I would have gone to another beach.	Model Predictions, weighted by predicted trips: I would not have gone to any beach.
Bacterial warning- day of trip	19.0	34.8	46.2	16.95	83.03	0.02
-Lifted 1 day before trip	34.6	32.0	33.5	32.91	67.07	0.016
-Lifted 3 days before trip	52.6	25.8	21.6	57.60	42.39	0.01
-Lifted 6 days before trip	76.2	11.4	12.4	77.9	22.10	0.005
HAB warning- day of trip	19.2	38.1	42.7	17.82	82.16	0.019
-Lifted 1 day before trip	39.0	30.0	31.0	36.32	63.37	0.015
-Lifted 3 days before trip	62.2	22.1	15.7	62.94	37.05	0.009
-Lifted 6 days before trip	80.1	11.0	8.9	79.67	20.33	0.005
HAB warning- next beach	56.3	15.2	28.6	56.92	43.07	0.01

APPENDIX O: Comparison of Impaired ASCs and Re-calibrated Baseline ASCs

Table O.1: Comparison of Impaired ASCs and Re-calibrated Baseline ASCs

Observed Warning	Site	Impaired ASC	Re-calibrated ASC	Absolute % change
Bacterial	Camp Perry Beach	-6.194	-6.128	1.1
	Century Park Beach	-6.286	-6.131	2.5
	Conneaut Beach	-5.939	-5.929	0.2
	East Harbor State Park	-5.935	-5.9	0.6
	Fairport Harbor Park Beach	-5.951	-5.939	0.2
	Geneva State Park	-5.926	-5.902	0.4
	Headlands Beach St. Park	-5.952	-5.94	0.2
	Lakeshore Park Beach	-6.114	-6.09	0.4
	Lakeview Park Beach	-6.075	-5.939	2.2
	Main Street Beach	-6.118	-5.977	2.3
	Maumee – Inland Beach	-6.264	-6.08	2.9
	Nickel Plate Beach	-6.06	-6.01	0.8
	Old Woman Creek Beach	-6.299	-6.248	0.8
	Sims Park Beach	-6.270	-6.174	1.5
	Sherod Park Beach	-6.337	-6.205	2.1
	Showse Park Beach	-6.431	-6.315	1.8
	Veteran's Beach	-6.300	-6.127	2.7
HAB	Edgewater Park Beach	-5.937	-5.913	0.4
	Euclid State Park	-6.176	-6.152	0.4
	Huntington Beach	-6.039	-6.013	0.4
	Maumee - Erie Beach	-6.144	-6.041	1.7

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