Valuing Lake Erie Beaches Using Value and Function Transfers

Leah H. Palm-Forster, Frank Lupi, and Min Chen

Two benefit-transfer approaches are used to estimate welfare losses from closure of Lake Erie beaches. We identify conditions for which the function transfer, which is more time-consuming and data-intensive, is worth the effort relative to a simple value transfer. The function transfer was essential for estimating beach demand (trips) and demand elasticity (change in trips); when evaluating individual beach closures with known trip demand, the two methods yielded similar results. Results produced by the two transfer methods deviated (up to 106 percent) when multiple beaches were closed simultaneously because value transfer did not account for the loss of beach substitutes.

Key Words: benefit function transfer, harmful algal blooms, random utility model, single-day trips, travel cost, value transfer

Benefit transfer is a valuation method in which values calculated for a resource in a primary study are used to estimate values for a similar resource at a different policy site. It is especially useful when answering urgent policy questions in situations in which constraints on time and/or money preclude the ability to collect primary data for the site in question because it allows researchers to respond quickly to a need for estimates of the value of the resource (Freeman, Herriges, and Kling 2014). One such site is the Western Lake Erie Basin, where beaches have had to be closed periodically in recent years because of harmful algal blooms (HABs) spurred primarily by phosphorus from agricultural run-off. The algae (*Microcystis sp.*) produce a toxin that is dangerous for humans, pets, and wildlife, and policymakers and stakeholders urgently need information regarding the causes and impacts of the blooms (International Joint Commission (IJC) 2014).

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We apply two benefit-transfer methods—value transfer and function transfer—to estimate the value of Lake Erie's beaches and then analyze the relative merits of those methods when the availability of behavioral and economic data in the policy setting and the scale of the environmental damage being assessed (the number of beach sites closed) vary. When selecting a benefit-transfer method, researchers face a tradeoff between the simplicity of a value transfer and the ability of a function transfer to represent the unique characteristics of the policy site and the affected population more accurately. Our study contributes to an understanding of the relative advantages and disadvantages of each method for various policy environments.

The simplest method is value transfer, which involves assigning a single point estimate of value from a study site to a policy site. Value transfer is quick and straightforward but does not account for differences between the sites and assumes that the conditions of the study site are representative of the conditions of the policy site. So, for example, value transfer does not capture how choice sets differ. In the case of Lake Erie beaches, accounting for the availability of alternative beach sites is important—fewer sites in the choice set limit the substitute beaches available when some beaches are closed and can lead to substantial welfare losses.

Benefit function transfer is a more complex approach in which a value function estimated in one or more primary studies is used to value a resource at a different policy site (Boyle et al. 2010). Broadly speaking, function transfers are preferable to value transfers because they are more flexible and can account for heterogeneous population characteristics and amenity attributes (Kaul et al. 2013, Boyle et al. 2010, Johnston and Rosenberger 2010, Brouwer and Spaninks 1999). However, function transfers are more time-consuming and require additional data about the policy site to calibrate the value function.

When conducting a benefit-transfer study, researchers must decide if the function transfer is worth the additional time and effort required. To evaluate the merit of the more complicated transfer method, we compare estimates of welfare losses from the closing of Lake Erie beaches using a value transfer and a function transfer. We estimate losses for single closures for each public Lake Erie beach site along the Michigan and Ohio coasts and for simultaneous regional closures of groups of beaches. Parsons et al. (2009) showed that group closures cause greater per-trip welfare losses than individual closures. In Lake Erie, bacterial contamination typically leads to one or a small number of beaches being closed while HABs typically affect much larger areas. We determine how the transfer method and number of beaches closed affect the value estimates in hypothetical closure scenarios.

We find that function transfer is preferred over value transfer to estimate trip demand when reliable data about trips are not available and to estimate welfare losses from regional closures. When transferring values from travel-cost models, our Lake Erie application shows that function transfer is essential for

estimating beach demand (as trips) and demand elasticity (as change in trips). When the elasticity of trip demand is known and closures affect only a small number of beaches, the two methods produce similar results. Deviation between the estimates increases exponentially as the number of beaches closed increases. In addition, when conditions such as HABs significantly change the choice set of beaches, a benefit-function transfer is preferred since it more fully accounts for site-substitution effects and trip elasticity. If benefit function transfer is infeasible, identifying a study site with a comparable scale of beach closures to that of the policy site will facilitate a more applicable value transfer.

Valuing Recreational Sites

In the United States and Europe, government agencies commonly require completion of benefit-cost analyses to evaluate the potential impacts of proposed policies and management plans (Boyle et al. 2010, Johnston and Rosenberger 2010). Since constraints on time and funding often preclude the possibility of primary studies, the analyses often are based on benefit transfers. The use of transfer approaches dates back to the 1960s. In recent years, however, demand for more-reliable benefit-transfer methods has spurred development of more-sophisticated approaches (Brookshire and Neill 1992, Desvousges, Johnson, and Banzhaf 1998, Wilson and Hoehn 2006, Rolfe and Bennett 2006, Navrud and Ready 2007, Boyle et al. 2010, Johnston and Rosenberger 2010, Johnston et al. 2015) and identification of best practices in the form of a generally accepted protocol (Boyle et al. 2010).

Much of the research so far has focused on how to reduce transfer error: the difference between the true valuation of the policy resource and the valuation estimated using benefit transfer. The consensus from that research is that the study site and policy site should be as similar as possible in terms of populations, resources, markets, and site attributes and that function transfers are more accurate than value transfers (Boyle et al. 2010). However, some studies have suggested that function transfers do not always outperform value transfers (Barton 2002).

Both supply-side and demand-side factors affect the value of recreational amenities at study and policy sites (Freeman, Herriges, and Kling 2014). Supply-side factors include amenity characteristics such as onsite parking and the length of the beach while demand-side factors refer to characteristics of the people who value the resource, including their preferences and socioeconomic characteristics. The preference for function transfer is largely attributable to the flexibility it provides in accounting for heterogeneity in amenities and population characteristics, thus reducing transfer errors (Kaul et al. 2013, Rosenberger and Loomis 2003). However, the superior performance of function transfer relies on the assumption that the statistical relationships between independent and dependent variables used for the study site also apply to the policy site. Rosenberger and Loomis (2003)

presented validity tests for thirteen benefit-transfer studies and reported that function transfer was generally more accurate than value transfer, though the range of errors under both approaches was considerable (Rosenberger and Loomis 2003, p. 458, table 6).

Another benefit of function transfer is the ability to predict public demand for trips to the recreation site when there is a lack of primary data. Deacon and Kolstad (2000) emphasized the importance of estimating beach visits in the absence of environmental disasters to determine the status-quo level of trip demand but noted that such records of visits are rarely available.[1] They also stressed the importance of accounting for the availability of substitute sites since the presence (absence) of similar sites can decrease (increase) welfare losses when a beach is closed.

While use of function transfer and updated trip demand in behavioral models generally has been shown to reduce transfer error, the added value of incorporating more-complicated transfer approaches has varied. Zandersen, Termansen, and Jensen (2007), for example, transferred benefits of access to a recreational site over a twenty-year time horizon and showed that updating the demand for trips reduced transfer error by 282 percent on average compared to updating preferences only. Parsons and Kealy (1994) showed that estimates of recreation values from a function transfer came within 4 percent of the true values while the error rate for simple value transfers was 34 percent. They found that updated information about trip demand only minimally reduced the error rate for the value transfer.

Lake Erie Beaches and Harmful Algal Blooms

Spurred by excess phosphorus, a resurgence of eutrophication and HABs is threatening Lake Erie after a partial recovery in the mid-1990s (Johnson et al. 2014). The microcystin toxin produced from HABs harms ecosystems, contaminates drinking water supplies, forces closures of beaches, and reduces the value of fisheries, lakefront properties, and recreation sites. The largest recorded HAB in Lake Erie occurred in 2011 and drew international media attention (IJC 2014). In subsequent years, smaller persistent HAB events led to another expansive bloom in 2014 that contaminated drinking water sources for half a million people and triggered declaration of a state of emergency for three counties in the Toledo area.

In previous decades, the primary contributors of contaminants to Lake Erie were point sources such as factories and water treatment plants, but the more-recent events were caused by nutrients emitted from nonpoint sources such as agricultural production and lawns (IJC 2014) and involved thousands

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[1] Deacon and Kolstad (2000) highlighted the challenges associated with acquiring visitation data. When beaches have entry fees or controlled access points, estimating attendance can be relatively straightforward, but many beaches do not have such controls.

of potential polluters (farmers and homeowners). Consequently, policies designed to limit such pollution are expensive and administratively challenging so it is important to understand the potential costs and benefits of a policy to determine whether it is economically worthwhile. In 2014, the federal government appropriated more than $2 million in emergency funding to reduce run-off in the Western Lake Erie Basin through agricultural conservation programs that limit losses of phosphorus. The resulting influx of state, federal, and private spending has spurred stakeholders to demand timely information about the value of benefits generated by HAB mitigation programs.

Few studies have estimated recreation values for Lake Erie beaches, and an understanding of those values is essential for efforts to estimate the economic impacts of HABs accurately. In the mid-1990s, several studies examined select beach locations along the Ohio coast. Sohngen, Lichtkoppler, and Bielen (1999) studied two popular Lake Erie beaches, Maumee Bay State Park and Headlands Beach State Park, and estimated average values for single-day trips of $15.50 for Headlands Beach and $25.50 for Maumee Bay Beach in 1998 dollars. Using the same data set, Murray, Sohngen, and Pendleton (2001) examined the impact of beach advisories on welfare for fifteen Lake Erie beaches. They found that the average seasonal benefit of a reduction in seasonal advisories by one event was $28 per visitor, which amounted to $3.2 million per year for the fifteen beaches combined.

Methods

Benefit transfer allows us to estimate welfare losses from hypothetical beach closures in response to HABs at the policy site, the western and central basins of Lake Erie. We transfer beach values and apply an estimated benefit function from a study by Chen (2013) that valued Great Lakes beaches using a repeated random utility model and that explained Michigan residents' visits to beaches along the Michigan coast at Lakes Michigan, Huron, St. Clair, and Erie. We conduct the value transfer by predicting the number of displaced trips to Lake Erie beaches and multiplying that number by Chen's estimated average per-trip value. For our function transfer, we update Chen's repeated nested logit model with data on Lake Erie beach amenities and census tracts that characterize potential beach visitors from Michigan, Ohio, and Indiana.

Value transfers require estimates of trip demand and the elasticity of that demand, but current data on visits were not available for the majority of the Lake Erie beaches. We use Chen's model to generate predictions about the number of trips taken to each beach. The repeated random utility model can predict trip demand because it captures both site choices and participation decisions. And since the model was estimated for the entire adult population of Michigan, we can use it to predict the average number of trips for the population of the policy site.

Chen's (2013) model is amenable to using census data for the function transfer. Using coefficients from the repeated nested logit model, we transfer the functions to estimate demand for single-day trips to Lake Erie beaches using population-weighted demographic data on potential beach users collected from five-year estimates in the 2012 American Community Survey (U.S. Census Bureau 2014). Our policy area encompasses 2,936 census tracts in Ohio, 1,702 census tracts in Michigan, and 102 census tracts in Indiana, and the universal choice set (the set of beaches that could have been visited by someone in the policy population) is comprised of 424 beaches located in Michigan and Ohio.

The Random Utility Model

We apply Chen's (2013) random utility model, which is illustrated in Figure 1. With a choice set of *J* beaches, person *n* will choose to visit beach *j* on lake *k* in choice occasion *t* if that beach provides greater utility than all of the choice alternatives (other beaches), *i*:

(1) $U_{njkt} > U_{nikt},\ \forall i \neq j,\ \forall k.$

Utility consists of a deterministic portion, V_{njkt}, that depends on observable characteristics, including the "price," and a random portion, ε_{njkt}, that is not observed by the researcher:

(2) $U_{njkt} = V_{njkt} + \varepsilon_{njkt}.$
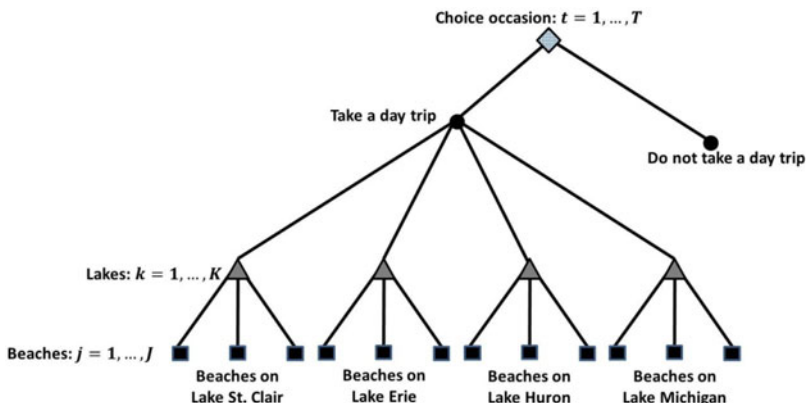
Figure 1. Structure of the Repeated Nested Logit Model

In the model, V_{njkt} depends on the trip price (the travel cost) and the beaches' characteristics:

$$(3) \qquad V_{njkt} = \beta_p \times price_{njk} + \beta_q \times beachquality_{jkt}$$

$$= \beta_{tc} \times travelcost_{njk} + \beta_l \times \log(beachlength_{jk}) + \beta_t \times temperature_{jkt}$$
$$+ \beta_{cd} \times closuredays2010_{jk} + \beta_r \times regionaldummies_{jk}.$$

The β parameters are presented in Table 1. Table 1 also presents the demographic variables that were used to predict participation (i.e., taking a beach trip) using the repeated logit model (see Figure 1).

When the random portion of utility (ε_{njkt}) is independently and identically distributed as generalized extreme values, the probability that individual n will choose beach j on lake k at time t is given by a nested logit. In the repeated nested-logit model, the unconditional probability of person n visiting beach j on lake k on day t is

$$(4) \qquad P_{nt}(j,\, k) = P_{nt}(trip)\, P_{nt}(k|trip)\, P_{nt}(j|k,\, trip)$$

$$= \frac{e^{\frac{V_{njkt}}{\lambda}} \left(\sum_{l=1}^{J_k} e^{\frac{V_{nlkt}}{\lambda}} \right)^{\frac{\lambda}{\sigma} - 1} \left(\sum_{m=1}^{K} \left(\sum_{l=1}^{J_m} e^{\frac{V_{nlmt}}{\lambda}} \right)^{\lambda/\sigma} \right)^{\sigma - 1}}{e^{V_{nt,no\ trip}} + \left(\sum_{m=1}^{K} \left(\sum_{l=1}^{J_m} e^{\frac{V_{nlmt}}{\lambda}} \right)^{\lambda/\sigma} \right)^{\sigma}}.$$

In this specification, λ is the lake-level nesting parameter, σ is the trip-level nesting parameter, and λ measures the degree to which the beaches in a given nest are similar. Higher values of λ indicate relatively less correlation (more independence) among the alternatives in the nest. The trip-level nesting parameter, σ, measures the degree to which the alternative of taking a beach trip differs from the choice not to take a beach trip.

Predicting Trips

We use Chen's (2013) model[2] to predict the number of trips taken to each beach site during summer months (May 27 through September 30) in 2010 by residents

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[2] The choice probabilities, parameter estimates, and welfare measures reported in Chen (2013) contained a scaling error that we corrected for the present study. The re-estimated model and results for the Chen study are available from the authors. All references here are to the corrected model.

in the policy area, which covers all of Ohio and parts of Michigan and Indiana. Since we do not have information about individuals or actual trips, we construct our observations using demographic characteristics for each census tract weighted by the number of adults in each census tract. We can thus predict the total number of day trips made to beach j at lake k in 2010 for each representative person n:

$$
(5) \qquad
\begin{aligned}
\hat{Y}_n(j,k) &= \sum_{t=1}^{T} \hat{P}_{nt}(j,k) \\
&= \hat{P}_{n,june}(j,k) \times 35 + \hat{P}_{n,july}(j,k) \times 31 \\
&\quad + \hat{P}_{n,aug}(j,k) \times 31 + \hat{P}_{n,sept}(j,k) \times 30.
\end{aligned}
$$

We aggregate the daily trips into monthly figures because the average water temperature varies during the summer and influences visitors' utility and trips. Trips made the last five days of May are included in June, generating 35 choice occasions (potential beach days) in June, 31 in July, 31 in August, and 30 in September.

To calculate the total number of trips to beach j at lake k, we multiply the trip estimates from equation 5 by the population of each census tract, n, and sum the census-tract estimates:

$$
(6) \qquad \widehat{Trips}(j,k) = \sum_{n=1}^{N} \hat{Y}_n(j,k) \times population_n.
$$

We also predict how the number of trips to beach j will change if one or more Lake Erie beaches closes.

$$
(7) \qquad \Delta\widehat{Trips}(j,k) = \widehat{Trips}(j,k)\Big|status\ quo - \widehat{Trips}(j,k)\Big|closure\ scenario
$$

Estimating Welfare Losses with Function Transfer

Welfare loss from closure of one or more sites is calculated using the estimated parameters from the nested logit model specified by Chen (2013) in the inclusive value (*IV*) formula for each choice occasion (Haab and McConnell 2002):

$$
(8) \qquad IV_{nt} = \ln\left(e^{V_{nt,notrip}} + \left(\sum_{m=1}^{K} \left(\sum_{l=1}^{J_m} e^{\frac{V_{nlmt}}{\lambda}} \right)^{\lambda/\sigma} \right)^{\sigma} \right).
$$

Over the entire season, an individual's inclusive value is the sum of the inclusive values in each choice occasion, t:

(9)

$$IV_n = \sum_{t=1}^{T} IV_{nt}$$
$$= IV_{n,june} \times 35 + IV_{n,july} \times 31 + IV_{n,aug} \times 31 + IV_{n,sept} \times 30.$$

We determine individuals' willingness to pay (WTP) to avoid closures of one or more beach sites. The beach closure(s) may result in people choosing an alternative beach site or deciding not to go to the beach. To calculate this WTP, we subtract the expected maximum utility in the closure scenario $\left(IV_n^1\right)$ from expected maximum utility without the closure scenario $\left(IV_n^0\right)$ and divide by the negative of the estimated parameter of the travel cost, $\hat{\beta}_{tc}$. The total change in welfare is calculated by aggregating the individuals' WTP estimates from the function transfer $\left(\widehat{WTP}_{FT}\right)$. In equation 10, we multiply the WTP of a representative individual in census tract n by the population of the census tract. Then, total WTP is calculated by summing the WTP values calculated for each of the 4,740 census tracts.

(10)

$$\Delta\hat{W}_{FT} = \widehat{WTP}_{FT} = \sum_{n=1}^{4,740} \frac{(IV_n^0 - IV_n^1)}{-\hat{\beta}_{tc}} * population_n$$

We calculate WTP per trip to a site by dividing the total WTP from equation 10 by the number of trips displaced (change in trips) from the site because of a closure, which was calculated in equation 7:

(11)

$$\widehat{WTP}_{FT,S} = \frac{\widehat{WTP}_{FT}}{\Delta\widehat{Trips}_S}.$$

In this formula, S denotes the set of beaches closed. When a beach is closed, all trips to that beach are lost so the number of displaced trips equals the number of all trips to the site predicted under status-quo conditions (equation 6).

Estimating Welfare Losses with Value Transfer

Multiple approaches can be used to estimate aggregate welfare measures using value transfer; the most appropriate method depends on the availability of data about displaced trips. If the number of trips displaced is known (provided by an external source), the analyst can multiply the average WTP to avoid losing a trip by the number of displaced trips. Since we do not have such information, we predict the number of displaced trips using Chen's (2013) site-choice model. Total WTP to avoid the closure scenario is calculated by multiplying the change in predicted trips (equation 7) by the transferred per-trip WTP value:

(12) $$\Delta \widehat{W}_{VT} = \widehat{WTP}_{VT} = \ \widetilde{WTP} \ per \ trip \times \Delta \widehat{Trips}_S$$

where $\Delta\widehat{Trips}_S$ represents trips lost to site(s) S that were closed. $\widetilde{WTP}$ is the per-trip WTP value estimated in the original study and transferred to the policy site.

This value transfer approach accounts for the popularity of each beach in terms of visits but does not account for differences in the number of choice alternatives or their quality. The number of choice alternatives in the original study and the policy site are quite different. Chen (2013) considered two southeast Michigan beaches in the Lake Erie nest while we consider two Michigan beaches and sixty-five Ohio beaches as substitutes in the same nest within the choice set. If we do not account for the additional alternatives available at the policy site, our model may overestimate the welfare loss incurred from closure of a typical Lake Erie beach because the relatively large number of alternatives in a nest allows individuals to avoid having to choose more-costly out-of-nest alternatives.

When trip data for the policy site are not available, the analyst can use aggregate welfare measures from the original study. In the context of our study, this would mean using the aggregate seasonal welfare losses estimated in Chen (2013). This approach accounts neither for the frequency of visits to the transfer site nor the availability of substitute sites. Another approach involves predicting displaced trips using a participation model, as we do in this study.

Data

Travel Cost

Both of the benefit-transfer methods employed in this study use the results from Chen's (2013) repeated nested logit to estimate welfare losses from hypothetical Lake Erie beach closures, but we do not limit the alternative choices to Lake Erie beaches. Our choice set consists of 357 beaches in the Lower Peninsula of Michigan along Lakes Michigan, Huron, and St. Clair and 67 Lake Erie beaches. All are public-access sites. The representative individuals' choice sets consist of beaches located within 250 miles of their residences[3] since the probability of an individual making a single-day trip of more than 250 miles is low (Parsons and Hauber 1998).[4] The choice set for the average census tract contains 162 sites.

To maintain consistency, we follow Chen (2013) and compute the travel cost by multiplying the round-trip driving distance by the average per-mile vehicle-operating cost ($0.2422 per mile) and adding the value of round-trip travel time at one-third of the household's income divided by 2,000 hours per year. The

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[3] In the model, the residence for each representative individual is located at the center of the individual's census tract.

[4] Chen (2013) found that only 1 percent of people taking day trips visited a beach located more than 250 miles away, and Murray et al. (1999) reported that visitors traveled 53.5 miles on average for a single-day trip to a Lake Erie beach.

## Table 1. Estimated Parameters from the Repeated Nested Logit Model Used for the Function Transfer

Variable	Estimate	t-Statistic
Beach Level of Nested Logit Model		
Travel cost	−0.026***	−82.61
Log(length)	0.075***	22.47
Temperature	0.033***	27.94
Closure days in 2010	−0.011***	−22.42
Lower peninsula northeast	−0.031	−0.53
Lower peninsula mideast	−0.733***	−12.01
Lower peninsula southeast	−0.786***	−12.67
Lower peninsula northwest	0.745***	12.64
Lower peninsula midwest	0.684***	11.31
Lower peninsula southwest	0.339***	5.60
Lake Level of Nested Logit Model		
Nesting parameter	0.383***	68.87
Trip/No-trip Level of Nested Logit Model: No Trip		
Nesting parameter	0.536***	53.20
Male	−0.124***	−8.04
Age	0.003***	4.43
White	−0.056**	−2.32
Education years	−0.105***	−33.40
Full-time employed	0.038**	2.08
Retired	0.187*	6.43
Children under seventeen years of age	0.067***	3.84
Constant	7.558***	62.89

Note: * represents a 10 percent significance level, ** represents a 5 percent significance level, and *** represents a 1 percent significance level.
Source: The corrected model based on Chen (2013) is available from the authors.

vehicle-operation cost per mile includes gasoline, maintenance, and tires plus per-mile depreciation as reported by the American Automobile Association (2011). It is important to note that Chen's calculation of marginal driving costs may be lower than the average driving cost used in other studies.[5]

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[5]   Chen omitted the cost of insurance since it is a sunk cost that does not increase because of additional miles driven to a beach and computed the marginal depreciation rate by determining

(a)   (b)
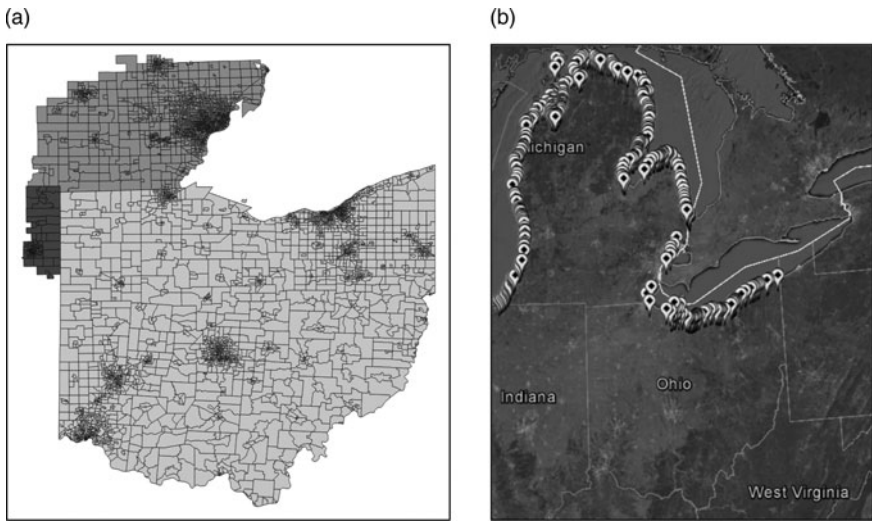
Figure 2. Location of the Census Tracts and Beaches

(a) Census tracts in Ohio, Michigan, and Indiana that reflect the policy site population.

(b) Great Lakes beaches in the universal choice set: 67 beaches along Lake Erie and 357 beaches along Lake Michigan and Lake Huron.

When comparing studies—and transferring values—it is important to consider the assumptions used in each study to compute travel costs, which can significantly affect the estimates of total welfare. We calculate the cost for average sedans, sport utility vehicles, and minivans. Chen computed a weighted average for Michigan vehicles by type based on a 2007 report by the Insurance Institute of Michigan that estimated the number of registered vehicles in the state. We assume that the distributions of car types in Michigan, Ohio, and Indiana are similar, thus allowing us to use the same estimated travel cost in all cases. To maintain consistency with the estimated parameters, we use the same 127 choice occasions as Chen: May 27 (Memorial Day weekend) through September 30, 2011.

Demographic Data

As shown in Figure 2a, the study area includes 2,936 census tracts in Ohio, 1,702 census tracts in Michigan east of Interstate 69, and 102 census tracts in Indiana east of Interstate 69 and north of Fort Wayne, Indiana. The people

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how much the total depreciation cost increased when yearly miles driven increased from 10,000 to 15,000 and dividing the change in depreciation by 5,000 miles. Using the average depreciation cost would increase the driving cost by nearly 20 cents per mile.

Table 2. Summary of Demographic Characteristics

Characteristic	From Chen	Current Benefit-transfer Study			
	Michigan	Ohio	Michigan	Indiana	Combined
Total population eighteen or older	7,561,510	8,811,640	7,561,510	4,883,604	21,256,754
Sample used in study	6,375 survey respondents	2,936 census tracts	1,702 census tracts	102 census tracts	4740 census tracts
People represented by census tracts	—	8,803,060	4,475,838	284,035	13,562,933
Demographic Characteristics of Sample Eighteen or Older					
Age (mean)	46.5	47.6	47.0	46.5	47.4
Income (mean in $1,000)	73,100	64,575	68,933	57,434	65,863
Education years (mean)	14.4	13.5	13.8	13.3	13.6
Male (percent)	48.6	48.0	47.8	48.3	48.0
White (percent)	86.4	85.4	75.8	85.1	82.2
Employed full-time (percent)	47.1	57.9	52.7	58.9	56.2
Percent retired—proxy is percent older than 65	23.7	18.6	17.2	17.1	18.1
Percent of children younger than seventeen	32.6	31.3	32.5	32.8	31.7

Source: Chen (2013) and U.S. Census Bureau (2014).

Table 3. Sources of Beach Data

Beach Attribute	Description	Source
Length	Length of beach in miles	Ohio Department of Health 2014, Michigan Department of Environmental Quality 2014, Google Earth 2014
Water temperature	Average monthly temperature of surface water at points closest to each beach	National Oceanic and Atmospheric Administration 2014
Closure days	Number of days that beach-specific advisories were issued in 2010[a]	Ohio Department of Health 2014, Michigan Department of Environmental Quality 2014
Regional dummies	Six binary variables that indicated the region in which the beach was located: northwest, midwest, southwest, northeast, mideast, and southeast.	Chen 2013
	Beaches in Ohio were assigned to the southeast region.	

[a]Although beach advisories are issued, visitors make up their own minds about beach use.

represented by these census tracts are relatively likely to visit Lake Erie beaches for day trips given their close proximity to the lake. We use the demographic attributes of each census tract to construct the observations, which are weighted by the population of the census tract so that the individual is representative of all residents in that area. The demographic data were collected from the 2008–2012 American Community Survey five-year estimates (U.S. Census Bureau 2014); Table 2 provides a summary of the population. The driving distances and travel times were computed using PC*Miler logistic mapping software to reflect miles and hours traveled on actual road networks between the center of each census tract and the 424 beaches in the universal choice set, which are depicted in Figure 2b.

Beach Data

Figure 2b presents the location of the beaches in the universal choice set. Measured beach attributes are the length of the beach, the average water temperature, and the number of closure days in 2010. The data for these characteristics were obtained from a variety of publicly available sources that are described in Table 3.

 Information about the presence of algal biomass would have allowed us to estimate welfare losses from marginal changes in water quality due to HABs.

Unfortunately, we cannot connect the presence of algal bloom biomass to beach visits, but we can estimate welfare losses from the blooms using beach closures. Future studies could add value to this research by estimating marginal welfare losses from varying levels of algal biomass at beaches.

Results

Predicting Trips

We first use equation 4 to predict the probability of any individual making a single-day trip to beach j at lake k in choice occasion t when no beaches are closed. We then use equation 5 to aggregate the probabilities of taking a single-day trip to beach j at lake k over all of the choice occasions to predict the seasonal number of single-day trips taken to beach j at lake k by each representative individual. By scaling those values up to the full population using equation 6, we predict the total number of single-day trips taken to each beach during the summer season.

To evaluate the predictions, we compare them to previously reported estimates for beaches at Headlands State Park and Maumee Bay State Park, which is located fifteen miles east of Toledo and would be a prime candidate for a beach closure in the event of a HAB.[6] Sohngen, Lichtkoppler, and Bielen (1999) reported approximately 238,000 visits to the beach at Maumee Bay State Park and 224,000 trips to the beach at Headlands State Park during summer months in 1998. Under normal (no HAB) conditions, our model predicts 269,352 day trips to Maumee (13 percent more) and 190,090 day trips to Headlands (15 percent fewer).

Comparison of Transfer Approaches for Single-beach Closures

We simulate 67 single-beach closures and use the seasonal inclusive values for the representative individuals from equation 9 to calculate WTP to avoid the loss of each beach site. Equation 10 estimates total WTP by all representative individuals to avoid lost trips due to a closure. We report three metrics: (i)

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[6]   In its 2010 annual report, the Ohio Department of Natural Resources (ODNR) (2010) estimated the number of visitor occasions at East Harbor State Park, Headlands State Park, and Geneva State Park at 1.56 million, 4.37 million, and 730,000, respectively. Averaging across all of the park sites included in the report, we find that 9.5 percent of the visits were beach occasions. However, the estimates listed in the ODNR report did not account for the fact that some parks have no beaches while others are popular beach destinations. Furthermore, the report's estimates did not differentiate between single-day and multiple-day trips to a particular site. When we apply our rough assumption of 9.5 percent of trips being beach visits, we find approximately 148,200, 415,150, and 69,350 beach trips for East Harbor, Headlands, and Geneva State Parks respectively. Our model predicts 129,482, 190,090, and 69,076 single-day trips to the same beaches.

WTP to avoid the loss of a single-day trip to each site (equation 11), (ii) welfare losses from closure of a beach for one day, and (iii) aggregate welfare losses from closure of a beach for the entire season.

Table 4 presents the resulting losses in welfare for seven of the single beach closures and compares the results from the value and function transfers. The value transfer uses the estimated WTP to avoid the loss of a single-day trip from Chen (2013): $18.08 adjusted for inflation to reflect 2015 dollars using a consumer price index (U.S. Bureau of Labor Statistics 2015).[7] The function transfer produces an average WTP of $15.91 and per-beach WTP that is 2–12 percent lower than WTP under Chen (2013). Overall, however, the estimates are similar.

Sohngen, Lichtkoppler, and Bielen's (1999) estimates for the beaches at Maumee Bay and Headlands State Parks were $25.60 and $15.50, respectively, per single-day trip—equivalent to $37.12 and $22.48 in 2015 dollars[8] (U.S. Bureau of Labor Statistics 2015). Using the benefit function transfer, we estimate per-trip values for those beaches of $16.39 and $16.05, respectively. Our considerably lower estimates are likely due in part to different assumptions regarding travel costs.

Table 4 also reports the results for a full-season closure of a beach. To estimate those welfare losses under the value transfer method, we use Chen's (2013) participation model to predict the number of visits in a season to each of the 67 beaches and then multiply that number by Chen's estimate of WTP per trip. The average full-season welfare losses per beach are $2.21 million under value transfer and $1.96 million under function transfer, a difference of 11 percent, and the deviations for the beaches are similar.

Overall, we find that the more-complicated function transfer provides no clear advantage over value transfer for evaluating welfare losses from closure of individual sites.

Comparison of Transfer Approaches for Regional Beach Closures

In the event of a HAB, multiple beaches could be closed, and the impacts of such regional closures would likely be different from the impacts of closing a single beach since there would be fewer choice alternatives to use as substitutes. As the number of alternative beaches declines, we expect that fewer total trips will be taken, resulting in trips being permanently lost instead of displaced. We therefore simulate group closures and compare the estimates of welfare loss from such closures under value transfer and function transfer.

We consider closure of four groups of Lake Erie beaches: 2 Michigan beaches, 6 western Lake Erie beaches, all 33 western Lake Erie beaches, and all 67 Lake Erie beaches in Michigan and Ohio. The resulting estimates of welfare losses

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[7] $1.05 (Y2015) = $1(Y2011) × 236/225 (price index 2015 / price index 2011).
[8] $1.45 (Y2015) = $1(Y2011) × 236/163 (price index 2015 / price index 1998).

## Table 4. Welfare Losses for Selected *Individual* Beach Closure Scenarios

Beach Closed	State	Basin Region	Per-trip-to-site Loss			Aggregate Seasonal Loss		
			2015 Dollars			Million 2015 Dollars		
			Value Transfer	Function Transfer	Percent Deviation	Value Transfer	Function Transfer	Percent Deviation
Sterling State Park	Michigan	Western	18.08	17.77	−1.7	12.32	12.11	−1.7
Luna Pier City Beach	Michigan	Western	18.08	16.44	−9.1	5.93	5.39	−9.1
Maumee Bay State Park	Ohio	Western	18.08	16.39	−9.3	4.87	4.42	−9.3
East Harbor State Park	Ohio	Western	18.08	15.90	−12.1	2.34	2.06	−12.1
Headlands State Park	Ohio	Central	18.08	16.05	−11.2	3.44	3.05	−11.2
Geneva State Park	Ohio	Central	18.08	15.95	−11.8	1.25	1.10	−11.8
Lakeshore Park	Ohio	Central	18.08	15.87	−12.2	0.50	0.44	−12.2
Average western basin	—	Western	18.08	15.92	−12.0	2.21	1.99	−10.1
Average central basin	—	Central	18.08	15.91	−12.0	2.20	1.94	−11.9
Average Lake Erie	—	—	18.08	15.91	−12.0	2.21	1.96	−11.0

Notes: The per-trip-to-site function transfer was computed using equation 11. The value transfer for the aggregate seasonal loss was computed using equation 12, and the function transfer was computed using equation 10. 2015 dollars were computed as $1.05 (Y2015) = $1(Y2011) × 236/225 (Price Index 2015 / Price Index 2011) (U.S. Bureau of Labor Statistics 2015).

Table 5. Welfare Losses for Selected *Regional* Beach Closure Scenarios

Closed Beaches	Per-site-trip Loss in 2015 Dollars				Aggregate Loss per Day in Thousand 2015 Dollars			
	Value Transfer	Function Transfer	Function Transfer 95 Percent Confidence Interval	Percent Deviation	Value Transfer	Function Transfer	Function Transfer 95 Percent Confidence Interval	Percent Deviation
2 Michigan beaches	18.08	19.01	[13.98; 23.13]	5.1	143.69	151.09	[111.09; 183.85]	5.1
6 western basin beaches	18.08	20.12	[18.88; 21.64]	11.3	233.45	259.78	[192.05; 324.50]	11.3
33 western basin beaches	18.08	23.46	[21.78; 25.50]	29.7	573.73	744.32	[547.40; 1,011.38]	29.7
67 Lake Erie beaches	18.08	37.21	[33.61; 42.73]	105.8	1,163.60	2,394.38	[1,808.46; 3,109.35]	105.8

Notes: The per-site-trip function transfer was computed using equation 11. The value transfer for the aggregate loss per day was computed using equation 12, and the function transfer was computed using equation 10. 2015 dollars were computed as $1.05 (Y2015) = $1(Y2011) \times 236/225$ (Price Index 2015 / Price Index 2011) (U.S. Bureau of Labor Statistics 2015).
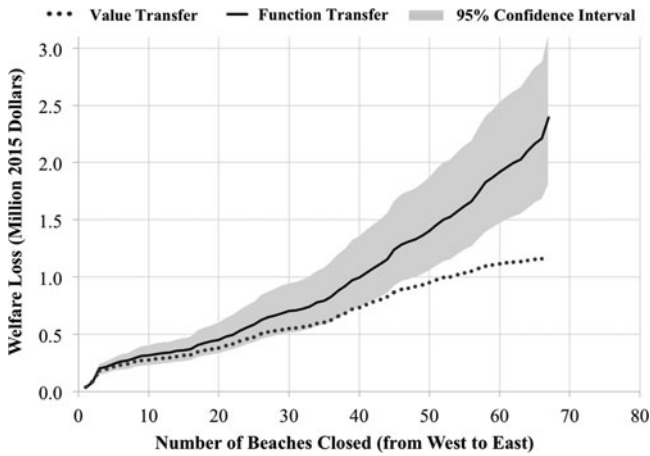
Figure 3. Comparison of Estimated Daily Welfare Losses for Simultaneous Single-day Beach Closures

from value and function transfers are presented in Table 5. We find much greater deviation between estimates generated by value and function transfers when groups of beaches are closed relative to single-beach closures. Furthermore, the value transfer approach, which predicted larger welfare losses than the function approach for individual closures, predicts significantly smaller welfare losses than the function approach for regional closures. The amount of deviation between the welfare estimates increases as the number of beaches closed rises. We find that the welfare losses estimated using function transfer are up to 106 percent greater than the estimates calculated with value transfer.

To further examine the scenario in which all 67 beaches are closed, we consider a case in which a bloom originates at the westernmost point of Lake Erie and spreads eastward, causing a sequential closing of beaches from west to east. Figure 3 presents the results of our estimates of the daily welfare losses for single-day closures, which increase exponentially with each additional beach closed, and 95-percent confidence intervals for the values from the function transfer constructed using 120 sets of beta coefficients estimated by bootstrapping the model from the original study.

Conclusions and Discussion

Benefit transfers are often viewed as simpler and more cost-effective alternatives to conducting primary valuation studies, but they require considerable care and careful analysis to obtain reliable value estimates. We use relatively simple value transfers and more time-consuming and data-intensive function transfers to

estimate welfare losses generated by closures of Lake Erie beaches and compare those estimates for both individual and regional beach closures. Our primary goal is to identify conditions under which the more time-consuming and data-intensive function transfer is worth the effort. Several prior studies (Parsons and Kealy 1994, Zandersen, Termansen, and Jensen 2007, Deacon and Kolstad 2000) have shown that the degree of transfer error for visits to recreational sites can be reduced by incorporating information about demand for trips and the set of trip substitutions available, but such behavioral information generally is not readily available and can be expensive and/or time-consuming to acquire.

Function transfers are preferable when demand for trips to the policy site is not well documented, as is the case for our study area. Of the 67 beaches included in our study, current data on demand for trips were available for only four and no data were available on sites used as substitutes or on the elasticity of trip demand. Transferring values from Chen's (2013) model allowed us to estimate the number of trips to Lake Erie beaches taken by residents of Ohio, Michigan, and Indiana and the individual sites visited under normal conditions when no beaches were closed. We then evaluated how trip demand changed and how much value would be lost under various beach-closure scenarios.

Our results suggest that the value and function transfer approaches yield nearly the same welfare estimates when considering closure of a single beach. However, the deviation in the two approaches' estimates increases exponentially as the number of beaches closed gets larger. In the case of regional closures, value transfer yields substantially lower welfare estimates than function transfer. The differences in the estimates from our value and function transfers are moderate because of the significant similarity between the primary and policy sites, but we show that deviation between the estimates increases significantly with the scale of closures. Benefit-transfer studies in which the primary and policy sites are less similar may find even larger differences in response to the scale of closures. We therefore conclude that function transfer is preferable when estimating welfare losses from beach closures at multiple scales.

Because we lack the data needed to estimate the "true" value of beach access, it is difficult to determine which model performs "best," but economic intuition points to two important benefits of using function transfer to estimate welfare losses from regional closures. First, by reflecting the price elasticity of the demand for trips, function transfer accounts for displaced (to substitute sites) and lost trips. Second, estimates of trip substitution better reflect the choice set of the policy site, which can be substantially different from the choice set of the primary study site. We also find that estimates from a value transfer are more accurate when the scales of beach closures at the primary study and policy sites are similar.

Lack of data resulted in several limitations. We are not able to estimate welfare losses from the presence of algal biomass at beaches that remained

open or the persistence of welfare losses after beaches reopen caused by degraded beach conditions (Deacon and Kolstad 2000). In addition, stigma associated with the poor quality of the beach can remain long after the beach is restored. Deacon and Kolstad (2000) referred to this as the "perceptually degraded period." Those welfare effects cannot be measured without data on how visits to the beach changed in response to a bloom that occurred months or years earlier. Future research on the long-term welfare impacts of HABs could make an important contribution to the literature, particularly if the studies could show how the value of the beaches changed specifically because of the HABs as opposed to other causes of beach degradation and closure.

Availability of a recent, well-documented study valuing Great Lakes beaches (Chen 2013) was an asset for our analysis. We recognize that researchers rarely find studies that are as amenable to benefit transfer between a study and policy site. Part of the value of Chen's (2013) research for function transfer is that it is a full-population model that can be readily transferred to other regions using census data. We conclude by highlighting three ways researchers can increase the usefulness of primary valuation studies to make the results more amenable to transfer.

The first is reporting useful value metrics that can be easily transferred to policy sites. Parsons et al. (2009), for example, calculated a loss-to-trips ratio that is easily transferred to other sites. It is also essential to report information about the choice sets used in the study so that characteristics of the alternatives in the study and policy sites can be compared. The size of the choice set and the attributes of site alternatives have an impact on welfare values, especially when evaluating regional resource changes.

The second recommendation is to report valuations for multiple scales of impact (e.g., single sites versus regions). A range of resource valuations will facilitate transfers when the scales of impact for the study and policy sites are different.

Finally, we recommend estimating models that can be used to generate demand for trips at future policy sites because information about displaced trips is often unavailable, unreliable, or outdated. In the context of random-utility-model travel-cost studies, visitors' participation can be included to understand the population who uses the recreational amenity. Since Chen (2013) used a population-wide survey to identify beach users, she could scale up the beach values to represent the entire Michigan population, and that allowed us to use a function transfer based on census data from other policy areas. Much of the work on benefit transfers has addressed valuation. An often-overlooked advantage of function transfer is the ability to generate trip estimates when data on trips for the policy site are either lacking or inadequate.

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