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Distributional effects of entry fees and taxation for financing public beaches

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Abstract

We use a detailed multi-site recreation demand model and general population dataset to assess the demand, welfare and distributional impacts of entrance pricing and taxation schemes to finance Great Lakes beach management. We compare the revenue resulting from uniform entry fees, or gate fees, across sites to additional state income tax that would generate equivalent revenues. We present empirical demand elasticities with respect to total prices inclusive of entry fees as well as elasticities with respect only to the fees. We find that demand is price elastic for total trips and for individual sites, with individual sites being significantly more elastic. However, over a broad range of entry fees, both total trips and individual site demands are elastic with respect to entry fees.

Keywords: Repeated random utility model, elasticity, Great Lakes beaches, gate fees

JEL codes: Q21, Q26, Q51

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Introduction

Public recreation sites such as coastal beaches are often managed to maximize public access rather than net benefits. In contrast to recreational activities like fishing and hunting (Walls and Ashenfarb, *this issue*; Lueck and Parker, *this issue*), for beaches there are no federal excise taxes or license fees to provide stable financial support for management or to protect quality. Moreover, public beaches often have several government entities involved in their management (e.g. local cities or counties), rather than one overarching state or federal agency. The absence of a dedicated funding source complicates the financing of beach management activities, as well as the sustainability of funding for beach safety actions such as surf warnings or water quality testing for bacterial contamination. Not surprisingly, there is a lack of literature on the implications of alternative ways to pay for maintaining beach recreation areas, although notable exceptions to this inattention are the issues of coastal erosion and beach nourishment (Kriesel et al. 2004; Gopalakrishnan et al. 2016).

To address this gap in our knowledge of the implications of beach recreational finance options, we use a detailed multi-site beach demand model and general population dataset to assess the demand, welfare and distributional impacts of entrance pricing and taxation schemes to finance beach management. In particular, we assess the recreation demand and welfare implications of uniform entry fees across all coastal sites in a state, and we compare these to state income tax levies that would generate revenue equivalent to each of these pricing schemes. Because we use a general population recreation demand model, for each financing policy we can assess the statewide revenue generation and trip responses across income groups.

This paper also contributes to the literature on recreation values for beach use, particularly in the Great Lakes. The Great Lakes are unique because they are the largest group of freshwater lakes on Earth. With the longest freshwater coastline in the country (over 1000 miles), Michigan has abundant public beaches along the Great Lakes' shoreline for its almost 10 million residents. Despite all this shoreline, there is very limited information from prior studies on demand for and the value of these freshwater beaches. In contrast, the economic value of ocean beaches has been investigated by many researchers (Bell and Leeworthy 1990; Parsons et al. 1999 & 2009; King 2002; Lew and Larson 2005; Leggett et al. 2018). One exception for the Great Lakes is Murray et al. (2001), although their study was applied to only 15 beaches on Lake Erie and may not be representative of beaches on the other areas of the Great Lakes. More recently, Chen (2013) developed a repeated nested logit model of single-day trips to 451 distinct Great Lakes beaches in Michigan and showed that site access values were between \$13-\$14 per single-day trip in 2012 dollars. The analysis reported here augments Chen's study using a model that includes both single and multiple day trips (following English et al., 2018), which results in values of \$26-\$27 per trip in 2012 dollars. The data and model structure cover the general population of Michigan, and the results show that, all else equal, high-income households are significantly more likely to take Great Lake beach trips.

In policy simulations we specifically compare effects of entry fees and general income taxes for financing public beaches. The response of total statewide trips to uniform entrance fees at all sites shows that total trip demand is elastic, with estimated total trip demand elasticities of about -1.5 and single site demand elasticities of about -3.4. However, with respect to the gate fees alone, both demands are inelastic over a wide range of fees. Since most beach and recreation demand studies are focused on welfare measurements, our elasticity estimate add to the limited information on recreation demand elasticities from multi-site models and contrast with older inelastic demands for single-site beach models (Phaneuf and Smith, 2005). We also show that under fixed entry fees across all sites, welfare losses are regressive: lower income users' losses as a share of income are significantly greater than higher income users. When comparing surplus losses for fixed site fee increases to revenue generated, the excess burden grows at a slightly increasing rate as fees rise, although interpretations of excess burden and the net benefits of user fees depends on the counterfactual and what is done with the fees (Banzhaf and Smith, *this issue*; Ji et al. *this issue*).

The remainder of the paper is organized as follows: Section 2 presents the model; Section 3 covers the survey and data used to estimate the model; and Section 4 presents results, including estimation results and the results of site pricing scenarios and income tax scenarios.

Model

The random utility model (RUM) developed by McFadden (1974) is a widely used structure for modeling multiple-site recreation demand that admits a wide range of alternative substitute sites. By including a "don't go" option in choice sets, the repeated RUM (RRUM) can explain both site choices and total trips per season in a unified framework, which is utility theoretic consistent for welfare analysis (Freeman III et al. 2014; Morey et al. 1993). This study uses a repeated RUM for Great Lake beach visits that was specified as a three-level nested logit model (Haab and McConnell, 2003) and originally reported in Cheng (2016). The nesting structure on a given choice occasion *t,* is depicted in Figure 1. On each choice occasion, Michigan resident *n* has the choice of whether to take a trip or not, which lake to choose, and where to go to the beach. The set of sites that are available to the beachgoer is denoted as the choice set *C.* The decision process can be visualized as simultaneously choosing among the trip nest options, *M*= {*Trip (G), No trip (No)*}, among the *L* lakes in the trip nest, *L* = {*Lake Erie,* *Lake St. Clair, Lake Huron, Lake Michigan}*, and among the *J* beaches at one of the lakes *l.* The choice is then repeated for *T* choice occasions across the beach season.

We define the beach season is as the period from Memorial Day weekend to September 30, which contains 126 days as our choice occasions. For any sampled respondent, if the sum of their reported trips in any month exceeds the total number of days in that month, the excess trips are trimmed (Morey et al. 1993). Less than 0.3% of the observations were trimmed due to exceeding the monthly choice occasions (Chen 2013).

Following English et al. (2018) and the recommendation of Lupi et al. (2020), we pool both day trip and overnight trips in the model. As in Bockstael et al. (1987), we treat time spent on the beach as endogenous and therefore it is not included in the cost of a visit. McConnell (1992) and English et al. (2019a) show that when time on-site is chosen as a part of recreation decisions, on-site time can be ignored in the demand specification and will not bias the demand estimation and welfare analysis of trips.

Since econometric details of RRUMs are presented in many applications (English et al., 2018; Morey et al., 1993), here we present only the choice probabilities and weighted log-likelihood function. The unconditional probability of taking a trip to beach *j* in time t is:

$$P_{jlG,nt} = \frac{\exp\left(\left(\frac{1}{\lambda} V_{ilG,nt}\right) * \left[\sum_{l \in L_m} \left[\sum_{j \in J_{lm}} exp\left(\frac{1}{\lambda} V_{jlG,nt}\right)\right]^{\frac{\lambda}{\rho}}\right]^{\rho-1} * \left[\sum_{j \in J_{lm}} exp\left(\frac{1}{\lambda} V_{jlG,nt}\right)\right]^{\frac{\lambda}{\rho}-1}}{\left[\sum_{k \in L_G} \left[\sum_{i \in J_{kG}} exp\left(\frac{1}{\lambda} V_{ikG,nt}\right)\right]^{\frac{\lambda}{\rho}}\right]^{\rho} + \exp\left(V_{No,n}\right)}$$

and the unconditional probability of *not* taking a trip to any beach is:

$$P_{No,nt} = \frac{\exp\,(V_{No,n})}{\left[\sum_{k\in L_G}\left[\sum_{i\in J_{kG}} exp\left(\frac{1}{\lambda}V_{ikG,nt}\right)\right]^{\frac{\lambda}{\rho}}\right]^{\rho} + \exp\,(V_{No,n})}.$$

The log-likelihood function is given by:

$$LL_{beach}^{RP} = \sum_{n=1}^{N}\sum_{t=1}^{T}\left[\sum_{l\in L_G}\sum_{j\in J_{kG}} w_n * y_{nt} * \ln\left(P_{jlG,nt}\right) + w_n * (1 - y_{nt}) * \ln\,(P_{No,nt})\right]$$

where $y_{nt} = 1$ if person *n* visited beach on occasion *t* and $y_{nt} = 0$ otherwise. The subscript *t* is retained because the model includes some time-varying site covariates. Finally, w_n is the weight for person *n* which is the product of three components (Cheng and Lupi, 2016). The first one is the sample weight, aiming to correct for sampling strata and raked for possible non-representativeness (Chen, 2013). The second weight corrects for multi-purpose overnight trips.[2] The final weight corrects for adjusted trip counts. In our web survey, after respondents finished their trip log section, we summarized the number of each type of trip they reported into a table, then verified whether the numbers in the table sound correct to them or not, and 3.6% adjusted their trip numbers. We used the ratio of the first reported number of trips to the changed number as the weight to correct for the trip adjustments (Cheng and Lupi, 2016).

[2] Since beachgoers might have multiple objectives for some trips, survey respondents were explicitly asked whether the main purpose of the randomly selected trip was for recreation, which was about 91% for short overnight trips and 92% for long overnight trips. To reflect that not all economic value accrues from beach recreation if there are multiple objectives involved (Yeh et al. 2006), we used the above-mentioned percentages as the corresponding weights to adjust all short overnight trips and long overnight trips downward. Thus, the number of trips a person reported as being short overnight were weighted by 0.91 and the ones they reported as longer were weighted by 0.92.

Another complication within the data is due to incomplete trip information where we only have partial information on the alternative chosen. For example, we do not know the exact beach visited for cases that only reported the nearest town or city to the beach or for cases that reported something general like "Lake Michigan." For these cases, we used the available information to form the joint probability of visiting a beach in the vicinity of that city or a beach on that lake to structurally identify the choices, akin to portions of English et al. (2018).

For our policy scenarios, we use the estimated model parameters and the above formulas to predict baseline trips and changes in trips for each scenario. To compute welfare measures for the pricing scenarios, we adapt the standard log-sum welfare measures from RRUMs to our nesting structure (English et al., 2018), and compute welfare for seasonal losses.

Survey Data and Model Specification

The data comes from the Great Lakes Beaches Survey[3], which was conducted in 2011 and 2012. The Great Lakes Beaches Survey was a statewide general population survey that consisted of two stages: a short screener survey, and then a web survey. To identify beachgoers, the screener survey was mailed to 32,230 Michigan adults who were randomly drawn from a Michigan driver's license list. To reduce potential self-selection bias, the screener survey covered a broad range of indoor and outdoor leisure activities, among which there was only one screening question for Great Lakes beach recreation. Respondents who answered that they had visited a Great Lakes beach during two summers in 2010 and 2011 were invited to take a follow-up web survey.

[3] See Min Chen (2013), Scott Weicksel (2012) for additional details regarding the survey sampling and implementation.

The web survey asked respondents for detailed monthly trip information on three types of trips from Memorial Day weekend to September 30, 2011: day trips (lasting a day or less), short overnight trips (less than four nights), and long overnight trips (four nights or more). For each of up to eight beaches visited, the survey elicited trips per month, as well as a trip count to any remaining beaches. In addition to trip information, respondents were asked for more detailed questions on up to two randomly selected trips, such as date, main purpose of the trip, etc. For trips with multiple beach destinations, we specify the destination as the beach where they spent the most time. Although most trips are day trips, short and long overnight trips are about 13% and 8% of the 19,284 total trips, respectively.

In the mail survey dataset with 9,591 observations, 3,838 indicated they did not visit any Great Lakes beaches in 2010 or 2011, so they are defined as “nonusers” for beach recreation but were retained for modeling. The 5,737 respondents that indicated they had visited a Great Lakes beach were invited to the web survey. There were 3,196 people who responded to the web survey for a response rate of about 59%. For demographics, respondents were asked if they were the person to whom the web survey was addressed or if they were another household member or “someone else”. To maintain consistent demographic information, we only kept the respondents to whom the web survey was addressed, which left us 2,537 effective respondents from the web survey. Following the definition in Shonkwiler and Shaw (1996), we define the respondents of the web survey who took at least one trip to Great Lakes beaches from Memorial Day weekend to September 30, 2011 as “users”, and those who had taken trips to Great Lakes beaches before but did not take any trip during the indicated season as “potential users”. Including the nonusers from the screener survey and users and potential users from the web survey, the effective sample size is 6,375. Among the 6,375 observations, there were 3,838 nonusers who had not taken any trips to Great Lakes beaches before. Applying the weights to the data, about 42% of the sample were nonusers during the sample season or in the two previous seasons.

The choice set is composed of reported beaches on Lake Erie, Lake St. Clair, Lake Huron and Lake Michigan, and does not include reported beaches that are on Lake Superior, on inland lakes or are outside of Michigan. After matching the reported beaches to the Michigan DEQ beach database, the universal choice set for each individual contains *J*=451 beaches (Figure 2) and the don't go alternative. On each occasion indirect utility for visiting beach *j* at lake *l* is:

$$V_{jlt} = \beta_{tc} * travel\ cost_{jl} + \beta_l * \log\left(beach\ length_{jl}\right) + \omega_t * temperature_{jlt} + \omega_{cd} * closure\ days\ of\ 2010_{jl} + \omega_r * regional\ dummies_{jl}.$$

The regional dummies, divide Michigan into 7 regions *R={UP, Upper Peninsula (the baseline), Lower Peninsula (LP) Northeast, LP Mid-East, LP Southeast, LP Northwest, LP Mid-West, LP Southwest}*. The indirect utility for individual *n* for *not* taking a trip is:

$$V_{No} = \gamma_{male} male + \gamma_{age} age + \gamma_{white} white + \gamma_{edu} edu + \gamma_{fulltime} fulltime + \gamma_{retire} retire + \gamma_{under17} under17 + \gamma_{income} Income + constant.$$

Table 1 reports descriptive statistics for site attributes in the indirect utility V_{jlt} and individual characteristics in V_{No}. Table 1 includes rows for the travel cost for all sites as well as for the visits. The computation of travel cost is:

$$Travel\ cost = distance \times 2 \times \$0.2422 + time \times 2 \times (income/2{,}000) \times (1/3)$$

where travel cost is the sum of driving cost and time cost. Round trip travel distance and round-trip travel time are calculated using PC Miler. Driving cost is calculated as $0.2422 per mile, based the 2011 AAA report and consists of per-mile marginal costs for fuel, tires, maintenance, and marginal depreciation for an average vehicle (Lupi et al., 2020). The value of time in recreation travel is approximated using the convention of one-third of hourly income which is annual income divided by 2000 hours per year of work.

The trip data as described above consists of the regular matched beach data as well as observations with partial information about the destinations visited. The resulting structure for the probabilities for this irregular data set cannot be accommodated using standard software packages for the nested logit model. Moreover, the panel data contains a time-variant variable, i.e., water temperature, and the choice set consists of 452 alternatives for each observation. Due to the complexity, the standard errors were bootstrapped.

Results

Estimation Results

The estimated parameters of the repeated nested logit model for all trip data are presented in Table 2. Results indicate travel cost has a negative and statistically significant effect on the probability of choosing a site, consistent with expectation. An increase in beach length increases the probability of choosing a beach at a decreasing rate; likewise, an increase in water temperature increases the probability of choosing a beach. The number of closure days in the previous year negatively affects the probability of visiting the beach. Although the estimates for these site variables make intuitive sense, we treat them here as controls to improve model fit and because they may be correlated with other omitted site characteristics. Regional dummies reveal that Lake Michigan attracts the most Michiganders, while Lake St. Clair and Lake Erie are less popular, all else equal.

The nesting parameters measure the degree of independence in nests of each level and are related to the correlation among alternatives within a nest. Results show that error terms for beaches are more correlated within each lake than across lakes. Both nesting parameters show that the nested logit provides a significant improvement over conditional logit.

The signs for all the estimated demographic parameters also make intuitive sense. In particular, the parameter for having higher income significantly and negatively affects the decision of not taking a trip in a choice occasion at a statistical confidence level of 99%. That is, Michiganders with higher incomes take more Great Lakes beach trips, all else equal. People with children 17 or under in their households were significantly less likely to take trips at the 5% level, a result consistent with findings for Gulf coast beaches (English et al., 2018) and boating (English et al. 2019b). At a 10% level of significance, all else equal, males take more trips while those employed fulltime take fewer trips.

For context, the model can be used to assess welfare benefits of beach access (i.e., for avoiding a beach closure). The model implies values for beach access of about \$26 to \$27 per lost trip to the closed site in 2012 dollars, which is slightly lower than from a model without the income effect (Cheng 2016). Closures that affect large areas such as an entire Great Lake will limit substitution possibilities and result in values per lost trip that can be over twice as large as single site closures. For example, Cheng (2016) shows that a closure of Lake Michigan induces substantial trip loss and yields a value of \$66 per lost trip (2012 dollars).

Beach Pricing and Financing Scenarios

For pricing policy scenarios, we simulate increases in gate fees where prices rise at all beaches by the same amount. We also compute state income tax rate changes that would generate equivalent revenue from the general population. For computing the state income tax that is equivalent to the revenue generated by each pricing scheme (reported in the last column of Table 3), it is noteworthy that Michigan has a single flat state income tax rate (4.25%) with fewer deductions than allowed for federal taxes, although the existing deductions mean the effective share of state incomes collected is lower than the tax rate. For the equivalent income tax calculations, we assume all resident adults would pay since they all face the same marginal rate.

In Table 3, the second column shows the change in trips as gate fees rise, which decline as expected. The third column shows the percentage loss of trips relative to the no fee baseline as the gate fee rises at all sites. The fourth column shows the arc elasticity (midpoint formula) for demand with respect to changes in the total price (gate fee plus travel cost), where each elasticity is computed for a one-dollar price change at all sites (e.g., the elasticity at the $10 fee was computed for a change from a $9 fee, not shown in the table). We find that total trip demand is elastic with respect to total price and averages -1.5 across the range of fees from one to twenty. However, note that with respect only to fees, total demand is inelastic with the fee elasticity averaging about -0.16 over the same range. Fee elasticity does not become elastic until fees reach about $60 at each site. This suggests a substantial potential to raise revenues assuming people respond to gate fees the same as travel costs and assuming the fees are imposed at all sites. Indeed, if we impose a fee at only one site, site demand is much more elastic to total price (with typical site demands having elasticity of -3.4) and less inelastic with respect only to fees (fee elasticity of -.38) for fees of one to twenty dollars. A typical site demand becomes elastic to fees imposed on it alone at about $26, lower than for fees at all sites due to the substitution potential.

The relative responsiveness to fees is depicted in Figure 3, which shows the effect of fees on relative demand for all sites and for a single site. In the figure, the “All sites” demand is for total demand to all sites with the fee at all sites, whereas the "Typical site" demand is for a single-site that faces a fee while other sites do not. To plot the relative demands on the same scale, each was normalized by dividing by their respective baseline trips without fees. As expected, demand at a single site is much more elastic to a fee than is total demand when all sites receive a fee, which has bearing on policies that apply fees differentially across sites.

The final columns of Table 3 show the revenue raised by fees and the statewide increase in income tax rate that would generate the equivalent revenue as the fees. Of note is the fact that while the burden of user-fees is borne by visitors, income tax changes are borne by all taxpayers. Notably, in our data, 42% had not visited a Great Lakes beach in the past three seasons.

Interestingly, the user fee is regressive when we look at the lost welfare as a percentage of income. In Table 4, we show the lost welfare and trips from the $10 fee (compared to no fee) as a percentage of income across income quartiles. The table shows that the share of trip losses is largest for the people in the lowest and highest income groups. Since the model estimates revealed a significant effect of income on trip taking, the result is potentially counter-intuitive. It can be explained by the observation that many of our other demographic variables are correlated with income in ways that influence trip taking. Specifically, compared to the lowest quartile, highest income individuals in our sample are significantly whiter (by 11%), more likely employed fulltime (by 40%), less retired (by 23%), and more likely to have children under 17 in the household (by 16%). Also relevant to trip taking are travel costs which increase with incomes and depend on where one lives relative to coasts. For example, Michigan has several large urban areas directly on, or in proximity to, the Great Lakes (e.g., Detroit) with lower incomes which both contribute to much lower travel costs, thereby increasing trip demand. Some of these areas also have higher unemployment, and these factors all combine to partially offset the fact that higher income people are more likely to take trips, all else equal. Consequently, welfare and trip losses from gate fees are borne relatively similarly across all income quartiles. Nevertheless, as a share of income, the welfare losses accrue significantly more to lower income households, making the fees regressive. Similar findings about the regressivity of recreation fees were found by von Haefen and Lupi (this issue) and Yi et al. (this issue) and for taxes on recreation gear (Walls and Ashenfarb, this issue).

Finally, Table 5 examines the excess burden associated with the fee increases.[4] As expected, the revenue increases are accompanied by larger surplus losses (i.e., the excess burden of the financing scheme). The results show that excess burden grows at a slightly increasing rate. Caution is warranted when interpreting these results since welfare loss depends on how the counterfactual is specified – much larger losses would be incurred if sites were to close due to lack of financing, so keeping the sites open at a fee is a welfare gain relative to closure. Alternatively, if sites would remain open at current quality, there are ways to craft gate fees that would not reduce welfare for visitors by reinvesting those fees into site quality in a manner that offsets the welfare effect of the fee (Banzhaf and Smith, *this issue*; Ji et al. *this issue*, Chan and Kotchen, *this issue*). Regardless, a key point to note in our comparison is that any gains due to keeping sites open (or reinvesting fees), accrue to the users, whereas the state income tax is borne by all residents.

Conclusion

Our policy simulations compare effects of uniform entry fees for all public Great Lake beaches in Michigan to a general income tax for financing beaches. We find total trip demand

[4] See Walls and Ashenfarb (this issue) for estimates of the potential excess burden of gear taxes.

across all sites is elastic, with estimated elasticities of about -1.5% and much higher for fees applied only to an individual site. Notably, over a large range of fees, total trip and individual site demands are inelastic with respect only to the fees. With uniform fees applied to all sites, we find all income quartiles incur roughly similar trip and welfare losses. However, as a share of income, welfare losses are regressive: lower income surplus losses are a significantly greater share of income than for higher incomes. Alternatively, the state's income tax is slightly progressive, yet all residents pay the income tax making this burden unavoidable. In contrast, although they may be regressive, with entry fees the burden falls entirely on users who can choose how to react. When comparing surplus losses for entry fees to revenue generated, the excess burden grows at a slightly increasing rate as fees rise, although as we discuss above, interpretations of excess burden and the net benefits of user fees depends on the counterfactual and what is done with the fees.

Our results contribute to the applied literature on recreation demand elasticities and the impact of site user fees in the context of contemporary multi-site recreation demand models, but our approach has limitations. Our approach assumes that visitors react to fees as they do to travel costs, which may not apply to all visitor types, and our modeling does not include congestion effects, which von Haefen and Lupi (this issue) show can overstate welfare loss and understate revenues of entry fees. In our model, income enters as a demographic variable in the "don't go" or "no trip" utility in the repeated RUM structure. While this allows us to investigate some distributional implications of the fees, more general forms of heterogeneity are fruitful areas of future work. Similarly, future work on distributional impacts of fees could examine fees applied differentially across sites.

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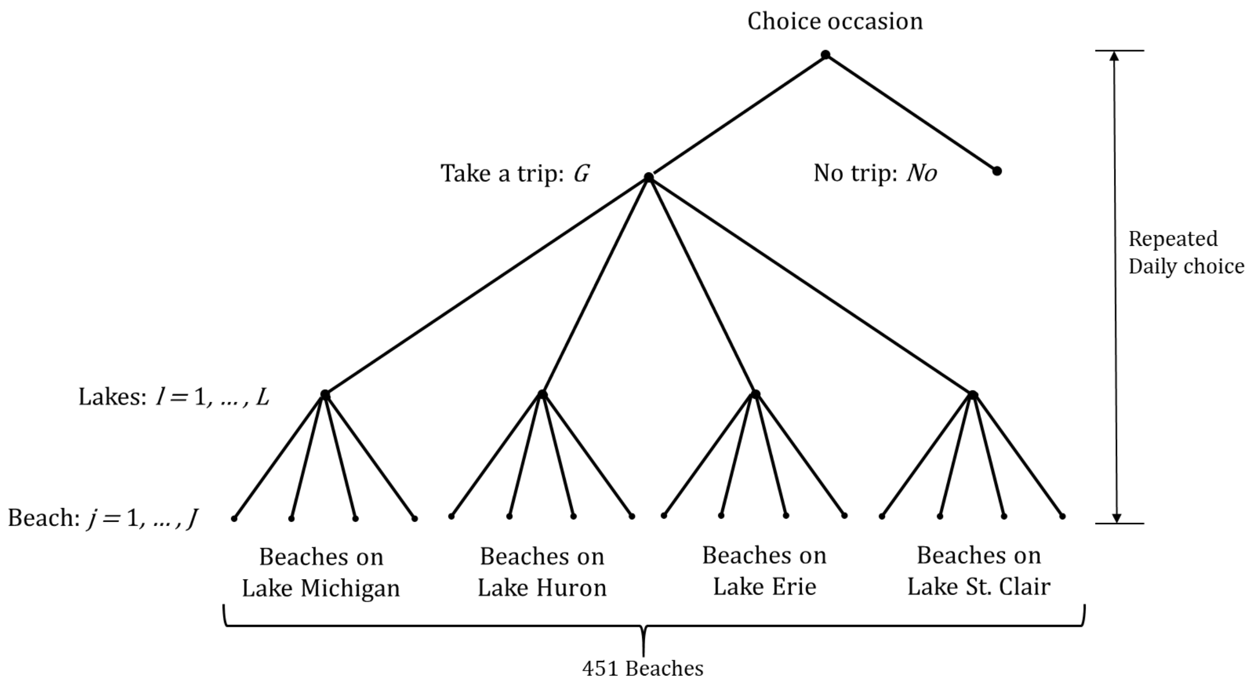

Figure 1. Repeated three level decision tree of beach recreation trip

Figure 2: Locations of 451 public great lakes beaches in demand model choice set

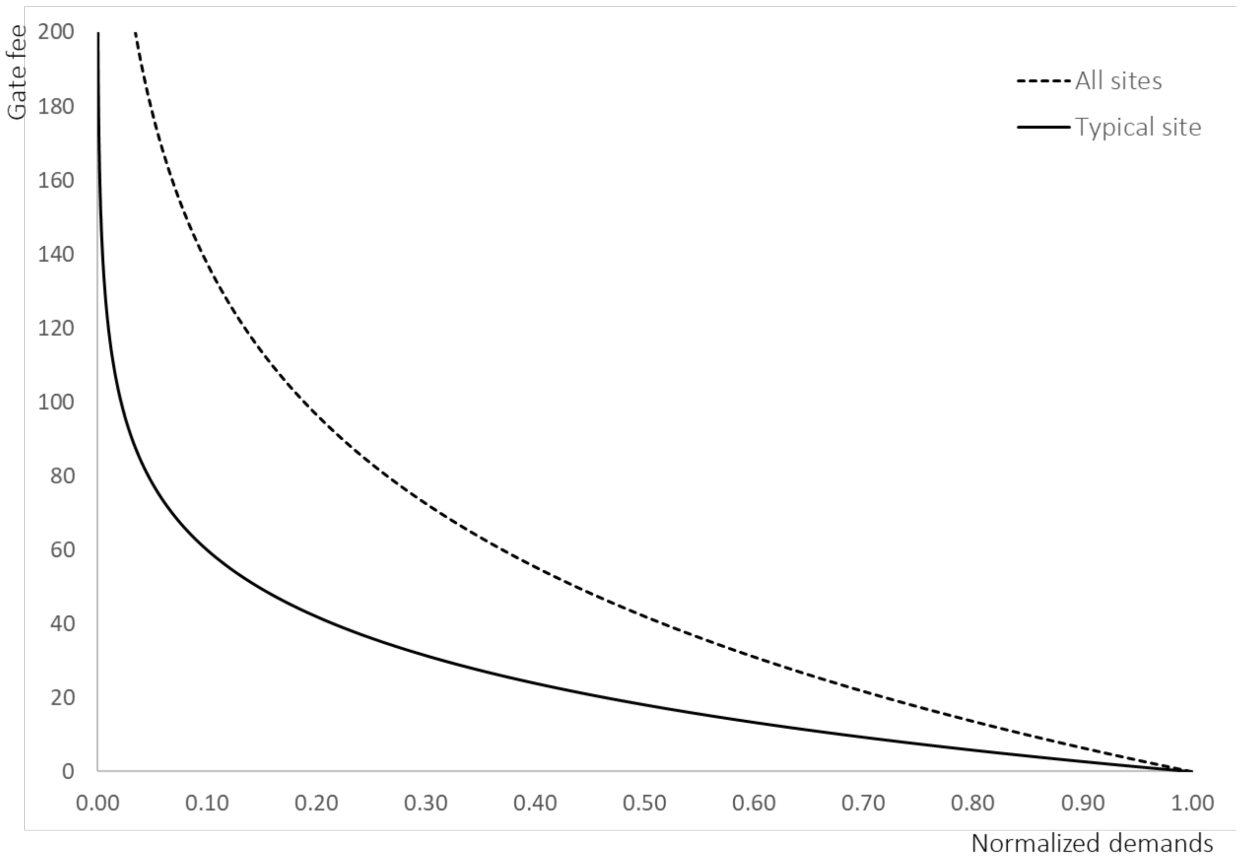

Figure 3: Demand for *All sites* when each has a gate fee and demand for a *Typical site* that solely faces a gate fee, with both demands normalized to one when there is no fee.

Table 1: Descriptive Statistics for Individual Characteristics and Site Attributes

Variables	Definition	Mean	Std. Dev	Min	Max
Socioeconomic characteristics (sample size=6375)					
Male	Dummy: 1=yes, 0=no	0.49	0.50	0	1
Age	Age	46.53	18.53	17	99
White	Dummy	0.86	0.34	0	1
Education years	Years of education	14.38	2.47	10	19
Fulltime employed	Full time employed, Dummy	0.47	0.49	0	1
Retired	Dummy	0.24	0.42	0	1
Children 17 and under	Children 17 and under, Dummy	0.33	0.47	0	1
Site Attributes (sites=451)					
Beach length	Miles of public shoreline	0.76	1.40	0.01	13.11
Temperature	June water temperature	55.50	4.24	48.87	72.57
	July water temperature	67.20	4.385	58.05	81.34
	August water temperature	67.76	4.59	58.49	78.93
	September water temperature	62.28	3.35	55.75	70.40
Closure days	Beach closure days from 2010	1.17	7.56	0	112
Regional dummy	LP northeast	0.20	0.40	0	1
	LP Mideast	0.09	0.29	0	1
	LP southeast	0.04	0.20	0	1
	LP northwest	0.33	0.47	0	1
	LP Midwest	0.06	0.24	0	1
	LP southwest	0.07	0.25	0	1
Travel cost	Travel cost for all j	203.8	120.9	0	1162
	Travel cost for visited j	79.58	211.9	0	1162

Table 2: Repeated RUM Beach Demand Model Estimation Results

Nesting Level	Variable	Estimates	Bootstrapped Standard Errors	t statistic
Beach level	Travel Cost	-0.017***	0.002	-10.24
	Log(Length)	0.093***	0.014	6.79
	Temperature	0.033***	0.004	8.07
	Closure Days of 2010	-0.013***	0.003	-3.73
	LP Northeast	0.040	0.143	0.28
	LP Mid-East	-0.588***	0.131	-4.48
	LP Southeast	-0.594***	0.158	-3.75
	LP Northwest	0.583***	0.109	5.36
	LP Mid-West	0.499***	0.124	4.04
	LP Southwest	0.120	0.111	1.08
Lake level	Nesting Parameter	0.443***	0.041	10.78
Trip level	Nesting Parameter	0.691***	0.076	9.06
No trip option	Male	-0.165*	0.089	-1.85
	Age	-0.002	0.003	-0.74
	White	0.196	0.194	1.01
	Education Years	-0.004	0.019	-0.21
	Fulltime Employed	0.174*	0.094	1.85
	Retired	0.108	0.146	0.74
	Children 17 and under	0.178**	0.080	2.23
	Income	-0.0065***	0.001	-7.60
	Constant	6.337***	0.392	16.146

Note: *10% significance level; **5% significance level; *** 1% significance level
Standard errors estimated via bootstrapping using 120 draws; all estimation and bootstrapping via MATLAB using MSU's HPCC Cluster.

Table 3: Trip responses, welfare effects, and revenue generation from uniform price increases, along with the added percentage points of state tax needed to generate equivalent revenue.[1]

Price increase at all sites	Total Trips (mil)	% loss of trips relative to no fee	Arc elasticity ($1 changes)	Revenue (mil $)	Equivalent % point change to statewide tax
$0	27.62				
$1	27.18	-1.64%	-1.31	27.18	0.0073
$2	26.74	-3.32%	-1.33	53.47	0.0143
$3	26.30	-5.02%	-1.35	78.91	0.0211
$4	25.88	-6.75%	-1.36	103.51	0.0277
$5	25.46	-8.51%	-1.38	127.29	0.0340
$10	23.46	-17.77%	-1.47	234.56	0.0627
$15	21.61	-27.85%	-1.55	324.10	0.0867
$20	19.90	-38.82%	-1.64	397.97	0.1064

[1] For comparison with other studies, average travel cost of visited sites is about $80 (Table 2).

Table 4: Welfare losses and trip losses as a percentage of income for $10 per site price increase across income quartiles.

Income Quartiles	Welfare Loss (mil $)	Welfare Loss per person ($)	Share of lost trips	Loss as a % of income	Revenue (mil $)
1	76.26	42.81	29.43%	0.31%	69.18
2	54.04	30.55	20.93%	0.09%	49.00
3	55.57	29.67	21.60%	0.05%	50.37
4	69.58	37.29	26.82%	0.03%	63.14

Table 5: Excess burden of access-based pricing (assuming sites would be open at the same quality absent the financing).

Fee at all sites	Revenue	CS Loss	Delta	Excess Burden
1	27.18	-27.48	-0.30	-1.1%
5	127.29	-132.95	-5.66	-4.4%
10	234.56	-255.41	-20.85	-8.9%
15	324.10	-368.24	-44.14	-13.6%
20	397.97	-472.18	-74.22	-18.6%