Two's Company, Three's a Crowd: Nonlinear Preferences for Crowding at Public Beaches

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Abstract

Beach recreation is popular and highly seasonal, which can result in crowding that impacts the visitor experience and strains local infrastructure. Understanding recreator preferences for crowding are fundamental for crafting strategies to manage it. This paper estimates preferences for crowding at public beaches in the Southeastern U.S. using a choice experiment. Respondents choose to visit one of two beaches or to forego a beach visit. The two beach visit alternatives differ in their distance from the respondent's home and their crowding levels. We measure crowding using a 100-point scale that maps simple illustrations and common beach experiences to percentages. We find that preferences for crowding are nonlinear. Above 20 percent crowding, respondents prefer less crowding, but below 20 percent crowding, respondents prefer more crowding. Our findings are consistent with early recreation demand research but contradict current practice, which typically assumes a constant marginal (dis)utility of crowding.

Keywords: Beach recreation; choice experiment; crowding

JEL Codes: Q20; Q26

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Introduction

U.S. beaches attract 3.4 billion visits annually and support coastal economies throughout the country (Houston, 2024). Their popularity and economic importance have inspired a substantial literature studying the demand for beach sites and their characteristics (Whitehead et al., 2008; Parsons et al. 2013). Daniel Lew made significant contributions to this literature. He conducted one of the first recreation analyses for beaches in Southern California (Lew and Larson, 2005a) and developed innovative approaches for addressing a persistent challenge in the recreation demand literature: modeling and estimating the value of leisure time (Lew and Larson, 2005b; Lew and Larson, 2008; Larson and Lew, 2014).

This paper focuses on another persistent challenge in the recreation demand literature: estimating preferences for crowding. Given the open-access nature of most recreation destinations, overcrowding can negatively impact visitors' experiences and strain local infrastructure. These effects are particularly apparent in beach recreation, given its widespread popularity and seasonality. Despite crowding's influence on recreation demand, it is difficult to estimate preferences for crowdedness at recreation sites, because crowded sites have other desirable attributes, which are often unobserved (Cesario, 1980). Furthermore, attempts to manage crowding at one site, through gate fees for example, cause crowding spillovers at other sites (von Haefen and Lupi, 2022). Understanding the role of crowding in beachgoer decision-making is, therefore, fundamental to benefit-cost analysis of alternative management policies.

We estimate preferences for crowding at public beaches using choice experiments. We survey recent visitors to beaches in the Southeast United States through a Qualtrics panel of respondents (N = 1,275). Beaches in our choice experiment have two attributes: crowding and distance from home. We explicitly state that all other attributes are constant across beaches. For each of six choice scenarios, respondents choose between three alternatives: (1) visiting a farther, less crowded beach, (2) visiting a closer, more crowded beach, or (3) foregoing a beach visit. We measure crowding on a 100-point visual crowding scale that maps simple illustrations and common beach experiences to percentages. Our choice experiment results reveal nonlinear and heterogeneous preferences for crowding. To explore nonlinear preferences for crowding, we specify a utility function that contains a quadratic polynomial of beach crowding levels. This specification allows preferences for crowding to change as a beach becomes more crowded. We find that respondents prefer to visit beaches that are around 20 percent crowded, all else equal. Below 20 percent crowding, respondents are willing to pay to increase crowding. Above 20 percent, increased crowding decreases willingness to pay for a beach visit. These preferences are robust to more flexible functional forms. Turning to heterogeneity, we find evidence that people who live far from a beach are more averse to both low and high levels of crowding than those living nearby. However, heterogeneity with respect to race, gender, income, and parental status is much less pronounced.

Our finding that preferences for crowding are nonlinear contributes to the broader literature on crowding in recreation demand models. It has long been acknowledged that ignoring crowding may bias WTP estimates for other site attributes (Cesario, 1980; von Haefen and Lupi, 2022). However, previous work has often assumed restrictive functional forms for crowding preferences. For example, Timmins and Murdock (2007) assume a constant marginal disutility from crowding, which, given our empirical findings, may not be realistic. Early in the recreation demand literature, Clawson and Knetsch (1963) discuss the possibility of disutility from both overcrowding and from isolation. Our findings confirm Clawson and Knetsch's conjecture in the context of beach recreation: when crowding levels are low, more crowding is actually desired.

We also introduce a novel scale for measuring crowding that may be of value in future studies. Previously, Timmins and Murdock (2007) and Phaneuf (2009) measure crowding using the count or share of visitors to a site. Bujosa et al. (2015) emphasize that density (e.g., visitors per unit of beach area) is more relevant to behavior than the number or share of visitors. Our crowding scale builds on Bujosa et al.'s work by providing respondents with a visual aid to convert experienced density levels to an intuitive 100-point scale. This tool could prove useful in future efforts to estimate preferences for crowding using either stated or revealed preference surveys.

Survey and Choice Experiment

Our data were collected using respondents from the Qualtrics online panel. Some studies have shown that stated preferences from convenience panels such as the Qualtrics panel can reasonably approximate results from probability-based samples (Johnston et al. 2017; Sandstrom-Mistry et al. 2023). Data were collected in two waves, with the first running from late December 2022 into early January 2023, and the second in May 2023. Across both waves, we collect a total sample of 1,275 responses. The recruitment targeted adults in the United States who had taken a coastal beach trip in the Southeastern U.S. over the last three years (at the time of collection, this was specified as trips since January 1, 2020). Beaches in the Southeastern U.S. were defined as sandy areas along the coastline from Texas to Virginia. Numerous data quality checks were implemented during data collection, including logic checks, speeding checks, and manual inspection of all open-ended fields to identify and eliminate bots or inattentive/inconsistent respondents.

Respondents were first asked about their typical beachgoing behavior over the past three years, including the distance from their home to their most-visited beach (measured in one-way driving distance), the beach location, what time of year they typically went to the beach, and the number of coastal beach trips they took. To ensure respondents understood our crowding measure as intended, the survey deliberately built up to our scale as follows. First, respondents were presented with information about beach crowding and were asked to rate their agreement with three crowding-related attitudinal statements. Then, respondents were shown three photos of real-life beaches with different levels of crowding. We asked respondents to analyze these photos by rating their agreement with the following statements: (1) there are many places to sit; (2) there are places to sit with plenty of personal space; and (3) this beach is crowded. Using this language, we then introduce respondents to our 100-point visual crowding scale (Figure 1). This scale depicts a generic beach with varying levels of person-figures to illustrate varying percentage levels of crowding. Thus, this is a depiction of the density of individuals at a coastal beach. Additionally, respondents were asked to use the 100-point crowding scale to rate the level of crowding they experienced on their most recent beach visit. This served to further increase respondent understanding of, and interaction with, our definition of crowding, a method of increasing survey comprehension (Sudman et al. 1996).

The choice experiment elicited stated preferences for crowding and distance to the nearest beach, holding all other beach attributes constant (see Figure 2 for example). Before beginning the choice experiment, we included a policy consequentiality reminder that stated, “Please respond carefully. Managers will use these responses to improve the visitor experience.” Respondents were asked to choose between (1) visiting a farther, less crowded beach, (2) visiting a closer, more crowded beach, or (3) foregoing a beach visit. Distance to nearest beach was presented as one-way driving distance measured in miles, while crowding was reported as a percentage and included a figure from the crowding scale to provide a visual reference for respondents (Figure 2).

Given the potentially wide ranges of driving distances in our sample and our desire to create realistic driving distances for the choice sets, the choice experiment design was stratified based on a respondent's driving distance to the nearest beach. There were three possible driving bins: less than 50 miles to the nearest beach, between 50 and 250 miles, or over 250 miles to the nearest beach. To create the levels for the distance attributes, we take a respondent's reported distance to the "coastal beach in the Southeastern U.S. that is nearest to [their] home" and randomly add one of the mileages shown in Table 1. The more distant respondents lived from a beach, the wider the range of potential distances that appeared in their hypothetical choice sets. Possible crowding levels are the same for all distances, ranging from 5 percent crowded to 95 percent crowded. The experimental design for the combinations of driving distances and crowding that appear in the choice sets were constructed using a Bayesian efficient design procedure in NGene. Each respondent was shown six choice sets.

To ensure the choice experiment is compatible with a traditional discrete choice travel cost framework, we translate the driving distances from the choice experiments into travel cost measures. Given some driving distances are quite large (e.g., over 1,000 miles one way), it is possible that respondents would choose to fly to the beach. Building on previous work by English et al. (2018), we therefore construct an expected travel cost measure that is a weighted average of flying and driving travel costs. This involved two steps. We first constructed driving travel costs using the driving distances from the experimental design, respondents' incomes, and per mile driving costs from AAA. We then translated driving travel costs into expected travel costs by constructing ratios of expected and driving travel costs from English et al. for different driving distance bins (e.g., 250 to 300 miles, 300 to 350 miles etc.). By taking the product of these ratios and driving travel costs, we recover estimates of expected travel costs and use them in our empirical specifications.

Descriptive Statistics

Figure 3 presents respondents' self-reported ZIP code of primary residence. Given the screening criteria of having taken a recent beach trip to the Southeastern U.S., it is unsurprising there is geographic concentration of respondents along the East and Gulf Coasts. Appendix table A1 presents additional descriptive statistics for the sample.

Following the choice experiment, we asked some separate crowding-related preference questions using a Likert scale, as shown in appendix table A2. Given that our choice experiments require respondents to make tradeoffs between distance and crowding, respondents' self-reported consideration of these characteristics can serve to validate the choice experiment results. Nearly 75 percent of respondents indicate they consider crowding when deciding what beach to visit on a typical trip, and 86 percent of respondents indicate they consider a beach's distance from their home when deciding what beach to visit. A majority, but relatively smaller percentage of respondents, 62.2 percent, agreed or strongly agreed that they would drive farther to recreate at a less crowded beach.

Model

Assume that at each choice occasion, t , an individual, i , chooses one of three choice alternatives indexed by $j \in \{0, 1, 2\}$. Alternative $j = 0$ is the outside option: foregoing a beach visit. The other two alternatives involve visiting a beach with a certain crowding level and travel cost. The utility individual i receives from choosing alternative $j = 0$ is:

$$U_{i0t} = \alpha_{0,i} + \alpha_{dem,i} D_i + \epsilon_{i0t} \tag{1}$$

where D_i is a vector of demographic variables. The $\alpha_{dem,i}$ coefficient vector allows the utility provided by the outside option to vary across demographic groups. The utility that individual i receives from alternative $j = 1$ or $j = 2$ is:

$$U_{ijt} = \alpha_{beach,i} + \alpha_{crowd1,i} crowd_{jt} + \alpha_{crowd2,i} crowd_{jt}^2 + \alpha_{TC,i} TC_{ijt} + \epsilon_{ijt} \tag{2}$$

where $crowd_{jt}$ denotes the crowding level and TC_{ijt} is the travel cost of accessing the beach. The intercept term, $\alpha_{beach,i}$, captures all attributes other than crowding and travel costs which, because respondents were told to assume that non-crowding attributes were the same across hypothetical beaches, are assumed to be constant. The parameter $\alpha_{TC,i}$ reflects the marginal disutility of travel costs, and the parameters $\alpha_{crowd1,i}$ and $\alpha_{crowd2,i}$ capture the individual-specific marginal utility (or disutility) of crowding. We assume the error term, ϵ_{ijt}, is independent and identically distributed across alternatives and choice occasions with a Type I extreme value distribution. We allow its variance to differ across individuals: $Var(\epsilon_{ijt}) = k_i^2(\pi^2/6)$, where k_i is the scale parameter.

Without changing the ordering of choice alternatives, we manipulate the utility function in equations (1) and (2) in two ways. First, we subtract each individual's $\alpha_{beach,i}$ coefficient from every choice alternative. Second, we explicitly introduce k_i into (1) and (2), and with no loss in generality, divide both equations by k_i. After these transformations, equation (1) becomes

$$\widetilde{U}_{i0t} = \beta_{0,i} + \beta_{dem,i} D_i + \tilde{\varepsilon}_{i0t} \tag{3}$$

where the intercept term $\beta_{0,i} = \left(\alpha_{0,i} - \alpha_{beach,i}\right)/k_i$ and the demographic coefficient vector is $\beta_{dem,i} = \alpha_{dem,i}/k_i$. Equation (2) becomes

$$\widetilde{U}_{ijt} = \beta_{crowd1,i}\, crowd_{jt} + \beta_{crowd2,i}\, crowd_{jt}^2 + \beta_{TC,i} TC_{ijt} + \tilde{\varepsilon}_{ijt} \tag{4}$$

where the β coefficients are defined similar to $\beta_{dem,i}$ in equation (3). The new error term, $\tilde{\varepsilon}_{ijt} = \epsilon_{ijt}/k_i$ is now independently and identically distributed across individuals, alternatives, and choice occasions and follows a normalized Type I extreme value distribution with $Var\left(\tilde{\varepsilon}_{ijt}\right) = \pi^2/6$.

We make several distributional assumptions for the random coefficients. We assume that crowding coefficients $\beta_{crowd1,i}$ and $\beta_{crowd2,i}$ follow a bivariate normal distribution with mean $\bar{\beta}_{crowd}$ and variance-covariance matrix, Σ_{crowd}. We further assume the travel cost coefficient follows an independent, lognormal distribution such that $\ln(\beta_{TC,i}) \sim N(\bar{\beta}_{TC}, \sigma_{TC}^2)$. Finally, we assume demographic coefficients are constant across individuals — i.e., $\beta_{dem,i} = \overline{\beta}_{dem}$ for all i.

Given these parameter distributions, the willingness to pay to reduce crowding is the ratio of a normally distributed random variable, which is a function of the crowding coefficients, and a lognormally distributed travel cost coefficient. We simulate mean willingness to pay by taking 100,000 random draws from the crowding and travel cost coefficient distributions. Specifically, the mean willingness to pay for a 10-percentage point *decrease* in crowding at beach j is

$$MWTP_j = -10\,\frac{1}{R}\sum_{r=1}^{R}\frac{(\beta_{crowd1,r} + 2\beta_{crowd2,r}\, crowd_j)}{\beta_{TC,r}} \tag{5}$$

where r indexes random draws from the crowding and travel cost coefficient distributions and $R = 100{,}000$.

Results

Nonlinear preferences for crowding

We first present evidence that preferences for crowding are nonlinear. Table 2 shows estimation results for three models, which we call the linear, quadratic, and semi-parametric models. In the linear model, utility is a linear function of crowding – i.e., we restrict $\beta_{crowd2,i} = 0$. In the quadratic and semi-parametric models, we relax this functional form assumption. The quadratic model adds a squared crowding term, and the semi-parametric model replaces the continuous crowding variable with 10 indicators, which uniquely identify each crowding level in the choice experiment (5, 10, 20, …, 90, 95). All three models include a lognormal travel cost coefficient, a normally distributed outside option/no beach indicator, and demographic variables.

Recall that we assume the travel cost coefficient follows a lognormal distribution, and thus, takes only negative values. The travel cost parameters in Table 1 represent the mean and standard deviation of the log of the travel cost coefficient. The mean of the travel cost coefficient itself is given by $-\exp\,(\bar{\beta}_{TC} + \sigma_{TC}^2/2)$. The travel cost parameter estimates are similar for the linear and quadratic models. In the semi-parametric model, the mean parameter estimate decreases, pushing the travel cost coefficient distribution towards zero.

Turning to the crowding parameters, the linear model's negative crowding coefficient suggests that respondents prefer less crowded beaches, on average. The mean of the quadratic crowding coefficient is statistically significant, suggesting that preferences for crowding are indeed nonlinear. Including the squared crowding term also flips the sign of the linear crowding coefficient. When crowding levels are low, respondents prefer more crowding, and as crowding levels rise, respondents eventually prefer less crowding. This same pattern is also apparent in the semi-parametric model (column 3), where 95 percent is the omitted crowding level. Utility peaks at 20 percent crowded, and crowding levels of 5 percent and 40 percent provide similar utility. The highest crowding levels, above 80 percent, provide the least utility.

All demographic variables are interacted with the indicator for the outside option – the no beach alternative. For these demographic variables, a positive estimate implies that on average the demographic group is more likely to select the outside option conditional on the other covariates. The signs of the demographic coefficients are similar across all three models. Older respondents are more likely to select the outside option and therefore less likely to visit a beach. Respondents with children, income above $100k, and full-time jobs are less likely to select the outside option. Coefficient estimates for race and ethnicity variables are not statistically significant. Finally, respondents living close to the beach are more likely to select the outside option than those living far away.

Figure 4 uses the crowding and travel cost parameter estimates to simulate the mean WTP to reduce crowding by 10 percentage points. The linear model suggests that people prefer less crowded beaches, which translates to a positive WTP to reduce crowding. The quadratic model allows WTP to vary across crowding levels, and the nonlinearity mirrors our results from table 2. At high crowding levels, people prefer less crowded beaches and WTP to reduce crowding is positive, but at low crowding levels, less than 25 percent, WTP to reduce crowding becomes negative. In other words, at low crowding levels, people are WTP to increase crowding. The quadratic model estimates imply a preferred level of crowding between 20 and 25 percent.

Figure 4 also plots WTP estimates from the semi-parametric model, which allows for a more flexible relationship between WTP and crowding. The semi-parametric estimates bolster our finding that preferences for crowding are nonlinear. Like the quadratic model, people are

WTP to increase crowding when crowding levels are low, and WTP to decrease crowding when crowding levels are high. Interestingly, WTP to reduce crowding flattens off; it is similar whether the beach is 30 percent or 90 percent crowded. The quadratic model does not capture this flattening off, which contributes to its higher WTP estimates at high crowding levels.

Heterogeneity by distance to nearest beach

We note that our WTP estimates are large relative to beach trip values published in the literature. For example, English et al. (2018) estimate the value of a lost beach user is approximately $75; like this paper, they field a national survey and focus on beaches in the Southeast. For a set of North Carolina beaches, Bin et al. (2005) value a user day between $18 and $133 per person per day for single day trips and $18 and $68 for multi-day trips.[1]

To explore what drives the magnitude of our WTP estimates, we investigate heterogeneity in WTP to reduce crowding. While WTP varies little across many demographics (appendix figure A1), we find strong evidence that people living farther from a beach are WTP more to change crowding levels. In figure 5, we estimate the quadratic crowding model for respondents living within different distances from a Southeast beach. The most restrictive distance threshold estimates the model for respondents living within 25 miles of a Southeast beach. These respondents are WTP $20, on average, to reduce crowding by 10 percentage points when a beach is 50 percent crowded and $40 when a beach is 80 percent crowded. For the full sample, these values quadruple; WTP is $85 when the beach is 50 percent crowded and $178 when it is 80 percent crowded.

[1] We convert these English et al. (2018) and Bin et al. (2005) estimates to 2023 USD to match the units of our willingness to pay estimates.

This heterogeneity in WTP may result because respondents living far from a SE beach are more likely to take multi-day trips. For respondents living within 50 miles of a beach, 26 percent of trips are multi-day trips. For respondents farther than 250 miles, the multi-day trip rate rises to 79 percent. The choice experiment asks respondents to consider a decision when they typically go to the beach, so the distant respondents may be considering multi-day crowding levels, not just a single day or even a few hours. Respondents are likely willing to pay more to reduce crowding for a longer duration.

Revisiting the magnitude of WTP to reduce crowding

Given the heterogeneity in WTP, comparing our initial WTP estimates to trip or user day values from the literature may be misleading. In our choice experiment, distant and local respondents are weighted equally, whereas trip values in the literature typically reflect the average value of a trip, and most trips are not long-distance. As a result, our above estimates weight distant respondents more heavily compared to previously reported average trip values. To make our WTP estimates more comparable to trip values from the literature, we create a trip-weighted measure of WTP. To do so, we estimate our model and calculate WTP separately for three subsamples of respondents: those living close (< 50 miles), medium (50 – 250 miles), and distant (> 250 miles) from Southeast beaches. For each of these subsamples, we also calculate the number of Southeast beach trips per respondent, which we use to weight the WTP from each distance group. For example, when the beach is 80 percent crowded, the close subsample is WTP \$40 to reduce crowding by 10 percentage points, the medium subsample is WTP \$89, and the distant subsample is WTP \$295. The close, medium, and distant subsamples account for 67 percent, 20 percent, and 13 percent of Southeast beach trips, so the trip-weighted WTP is $\$83 = 0.67 \times \$40 + 0.20 \times \$89 + 0.13 \times \$295$.

Figure 6, panel (a) shows WTP estimates from the quadratic model for the close, medium, and distant subsamples. Consistent with figure 5, respondents living closer to a Southeast beach are WTP less to change crowding levels. Interestingly, local and medium-distance respondents have only a slight distaste for low crowding levels. Panel (b) compares the trip-weighted WTP measure to mean WTP for the full sample. By shifting more weight to respondents living near a beach, trip-weighting reduces the magnitude of WTP to reduce crowding. For a 50 percent crowded beach, the mean WTP to reduce crowding by 10 percent is $85 for the pooled sample, while the trip-weighted mean WTP is only $41.

Conclusion

This paper estimates preferences for crowding on public beaches throughout the Southeastern U.S. using a choice experiment. Our most notable finding is that preferences for crowding are nonlinear. Respondents dislike crowded beaches, but they also dislike extreme isolation. Willingness to pay for a visit is highest at around 20 percent crowded. These results are robust to flexible functional forms. Additionally, we find evidence that willingness to pay to change crowding levels increases as respondents live farther from a beach.

These findings have implications for the recreation demand literature, where crowding has been a persistent challenge. All site attributes, observed and unobserved, impact crowding, and crowding implies that recreators' choices are interdependent. While the recreation demand literature has made progress in overcoming these challenges, most papers simplify modeling and estimation by assuming that crowding has a constant marginal disutility. That is, a marginal increase in crowding has the same disutility no matter how crowded a site is to begin with. Our findings contradict this assumption. Instead, our findings align with Clawson and Knetsch's (1963) early musings that recreators dislike both overcrowding and isolation.

Our results motivate several lines of future research. First, future research could estimate preferences for crowding in other recreation settings. Nonlinear preferences for crowding in beach recreation need not imply nonlinear preferences in the context of angling or hiking, for example. Second, more research is needed to understand equilibrium properties of recreation demand models when preferences for crowding are nonlinear. Timmins and Murdock (2007) and Bayer and Timmins (2005, 2007) discuss equilibrium properties of demand models that incorporate crowding, but all these papers assume a constant marginal utility/disutility of crowding.

Improving how recreation demand analyses incorporate crowding is critical for improving management of recreational resources. Crowding levels and perceptions depend not just on demand, but also on management strategies. Resource managers can influence crowding with gate fees and quota systems, as well as infrastructure improvements, such as adding parking or boat ramps. In many high-profile settings, many of these management strategies have already been implemented or are under consideration. For example, several U.S. National Parks require timed reservations for entry (Creany et al. 2024). Even though policies managing crowding are often contentious, their welfare impacts remain largely unclear.

References

Bayer, Patrick and Christopher Timmins. 2005. "On the equilibrium properties of locational sorting models." *Journal of Urban Economics* 57 (3): 462-477 https://doi.org/10.1016/j.jue.2004.12.008.

Bayer, Patrick and Christopher Timmins. 2007. "Estimating Equilibrium Models of Sorting across Locations." *The Economic Journal* 117 (518): 353-374.

Bujosa, Angel, Antoni Riera, Robert L. Hicks, and Kenneth E. McConnell. 2014. "Densities Rather than Shares: Improving the Measurement of Congestion in Recreation Demand Models." *Environmental and Resource Economics* 61 (April): 127–40. https://doi.org/10.1007/s10640-014-9785-9.

Cesario, Frank J. 1980. "Congestion and the Valuation of Recreation Benefits." *Land Economics* 56 (3): 329–38. https://doi.org/10.2307/3146035.

Clawson, Marion, and Jack L. Knetsch. 1963. "Outdoor Recreation Research: Some Concepts and Suggested Areas of Study." *Natural Resources Journal* 3 (2): 250–75.

Creany, Noah, Christopher A. Monz, and Scott M. Esser. 2024. "Understanding visitor attitudes towards the timed-entry reservation system in Rocky Mountain National Park: Contemporary managed access as a social-ecological system." *Journal of Outdoor Recreation and Tourism* 45: 100736. https://doi.org/10.1016/j.jort.2024.100736.

English, Eric, Roger H. von Haefen, Joseph A. Herriges, et al. 2018. "Estimating the Value of Lost Recreation Days from the Deepwater Horizon Oil Spill." *Journal of Environmental Economics and Management* 91 (2018): 26–45. https://doi.org/10.1016/j.jeem.2018.06.010.

Houston, James R. 2024. "The Economic Value of America's Beaches." *Shores & Beach* 92 (2): 33–43.

Johnston, Robert J., Kevin J. Boyle, Wiktor (Vic) Adamowicz, Jeff Bennett, Roy Brouwer, Trudy Ann Cameron, W. Michael Hanemann, Nick Hanley, Mandy Ryan, Riccardo Scarpa, Roger Tourangeau, and Christian A. Vossler. 2017. "Contemporary Guidance for Stated Preference Studies." *Journal of the Association of Environmental and Resource Economists* 4 (2): 319-405

Larson, Douglas M., and Daniel K. Lew. 2014. "The Opportunity Cost of Travel Time as a Noisy Wage Fraction." *American Journal of Agricultural Economics* 96 (2): 420–37. https://doi.org/10.1093/ajae/aat093.

Lew, Daniel K., and Douglas M. Larson. 2005a. "Valuing Recreation and Amenities at San Diego County Beaches." *Coastal Management* 33 (1): 71–86. https://doi.org/10.1080/08920750590883079.

Lew, Daniel K., and Douglas M. Larson. 2005b. "Accounting for Stochastic Shadow Values of Time in Discrete-Choice Recreation Demand Models." *Journal of Environmental Economics and Management* 50 (2): 341–61. https://doi.org/10.1016/j.jeem.2005.02.001.

Lew, Daniel K., and Douglas M. Larson. 2008. "Valuing a Beach Day with a Repeated Nested Logit Model of Participation, Site Choice, and Stochastic Time Value." *Marine Resource Economics* 23 (3): 233–52. https://doi.org/10.1086/mre.23.3.42629616.

Parsons, George R., Zhe Chen, Michael K. Hidrue, Naomi Standing, and Jonathan Lilley. 2013. "Valuing Beach Width for Recreational Use: Combining Revealed and Stated Preference

Data." *Marine Resource Economics* 28 (3): 221–41. https://doi.org/10.5950/0738-1360-28.3.221.

Phaneuf, Daniel J., Jared C. Carbone, and Joseph A. Herriges. 2009. "Non-Price Equilibria for Non-Marketed Goods." *Journal of Environmental Economics and Management* 57: 45–64. https://doi.org/10.1016/j.jeem.2008.09.002.

Sandstrom-Mistry, Kaitlynn, Frank Lupi, Hyunjung Kim, and Joseph A. Herriges. 2023. "Comparing Water Quality Valuation across Probability and non-Probability Samples." *Applied Economic Perspectives and Policy*45(2): 744–761. https://doi.org/10.1002/aepp.13375

Sudman, S., Bradburn, N.M., and Schwarz, N. 1996. Thinking about Answers: The Application of Cognitive Processes to Survey Methodology. Jossey-Bass, San Francisco, 304 pp, ISBN, 0-7879-0120-2

Timmins, Christopher, and Jennifer Murdock. 2007. "A Revealed Preference Approach to the Measurement of Congestion in Travel Cost Models." *Journal of Environmental Economics and Management* 53 (2): 230–49. https://doi.org/10.1016/j.jeem.2006.08.002.

von Haefen, Roger H., and Frank Lupi. 2022. "How Does Congestion Affect the Evaluation of Recreational Gate Fees? An Application to Gulf Coast Beaches." *Land Economics* 98 (3): 495–508. https://doi.org/10.3368/le.98.3.082721-0102.

Whitehead, John C., Christopher F. Dumas, Jim Herstine, Jeffery Hill, and Bob Buerger. 2008. "Valuing Beach Access and Width with Revealed and Stated Preference Data." *Marine Resource Economics* 23 (2): 119–35. https://doi.org/10.1086/mre.23.2.42629607.

Figures & Tables

Table 1: Choice Experiment Distance Level Changes Depending on Respondent Distance to Nearest Beach

	Distance to Nearest Beach < 50 Miles	Distance to Nearest Beach 50 – 250 Miles	Distance to Nearest Beach > 250 Miles
Each respondent's distance to their nearest beach plus the following levels	10, 25, 50, 100 miles	10, 50, 100, 250 miles	10, 100, 250, 500 miles

Table 2: Parameter estimates from linear, quadratic, and semi-parametric models

	1	2	3
Travel cost ($100s)	0.422	0.358	-0.081
	(0.076)	(0.069)	(0.082)
S.D. travel cost	1.048	0.987	0.969
	(0.105)	(0.077)	(0.097)
Crowding (10 p.p.)	-0.497	0.612	
	(0.023)	(0.060)	
Crowding (10 p.p.) squared		-0.135	
		(0.008)	
Crowding = 5%			1.855
			(0.105)
Crowding = 10%			2.455
			(0.118)
Crowding = 20%			2.617
			(0.114)
Crowding = 30%			2.107
			(0.126)
Crowding = 40%			1.795
			(0.115)
Crowding = 50%			1.607
			(0.103)
Crowding = 60%			0.900
			(0.151)
Crowding = 70%			0.535
			(0.107)
Crowding = 80%			-0.098
			(0.113)
Crowding = 90%			-0.493
			(0.087)
S.D. crowding	0.348	0.817	
	(0.019)	(0.090)	
S.D. crowding squared		0.103	
		(0.011)	
Corr(crowding, crowding squared)		-0.842	
		(0.033)	
No beach indicator	-3.711	-2.462	-0.139
	(0.502)	(0.448)	(0.304)
S.D. no beach indicator	1.374	1.682	1.322
	(0.173)	(0.189)	(0.120)
Interacted with no beach indicator			

Age 65+	0.623	1.045	0.465
	(0.249)	(0.271)	(0.164)
Has children	-0.762	-0.943	-0.645
	(0.292)	(0.325)	(0.187)
Employed full time	-0.819	-1.045	-0.605
	(0.272)	(0.302)	(0.163)
White	0.005	-0.076	0.305
	(0.320)	(0.349)	(0.201)
Hispanic/Latino	0.446	0.473	-0.055
	(0.444)	(0.457)	(0.292)
Income > $100k	-1.545	-1.760	-0.656
	(0.277)	(0.331)	(0.182)
Male	-0.098	-0.203	-0.279
	(0.241)	(0.254)	(0.152)
Distance to nearest beach (100s of miles)	-1.434	-1.635	-0.882
	(0.140)	(0.143)	(0.088)
Distance to nearest beach (100s of miles) squared	0.041	0.048	0.024
	(0.004)	(0.005)	(0.004)
N observations	22,950	22,950	22,950
Log-likelihood	-6032.8	-5696.9	-6416.9

Note: The table shows parameter estimates for the linear crowding model (column 1), the quadratic crowding model (column 2), and the semi-parametric model (column 3).

Figure 1: Crowding Scale

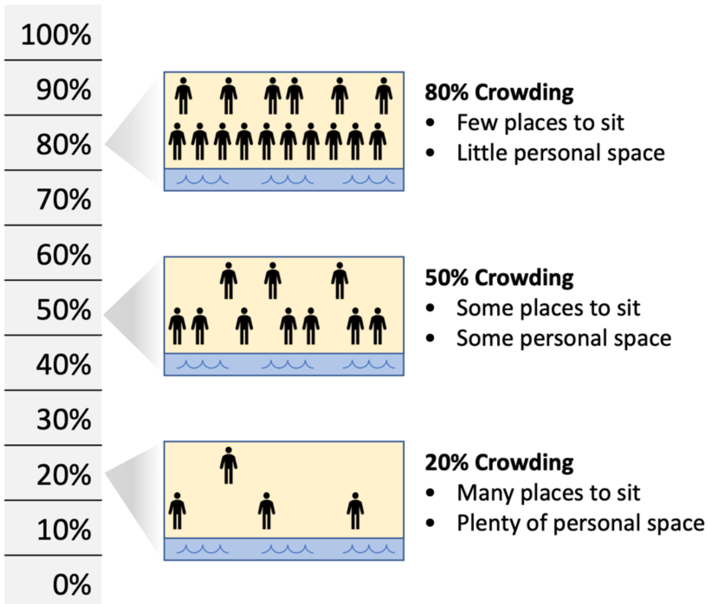


Figure 2: Sample Choice Experiment

Scenario 1 of 6

For this scenario, consider the two beaches in the table below.

- The two beaches, **Beach A** and **Beach B**, are located in the Southeastern US.
- The beaches differ in terms of their typical crowding and one-way driving distance from your home.
- In all other ways, the beaches are identical.

Assume that you are deciding whether to take a beach trip on a day when you typically go.

- Only Beach A and Beach B are available to visit.
- If you do not visit either beach, you will not take a beach trip. Instead, you will do something else with your time.

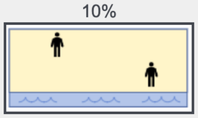
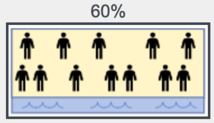
Attribute	Beach A	Beach B
Typical crowding %	10% 	60% 
Driving distance (one-way miles)	165	125
All other features	Same	Same

Figure 3: Map of Respondent Home ZIP Code

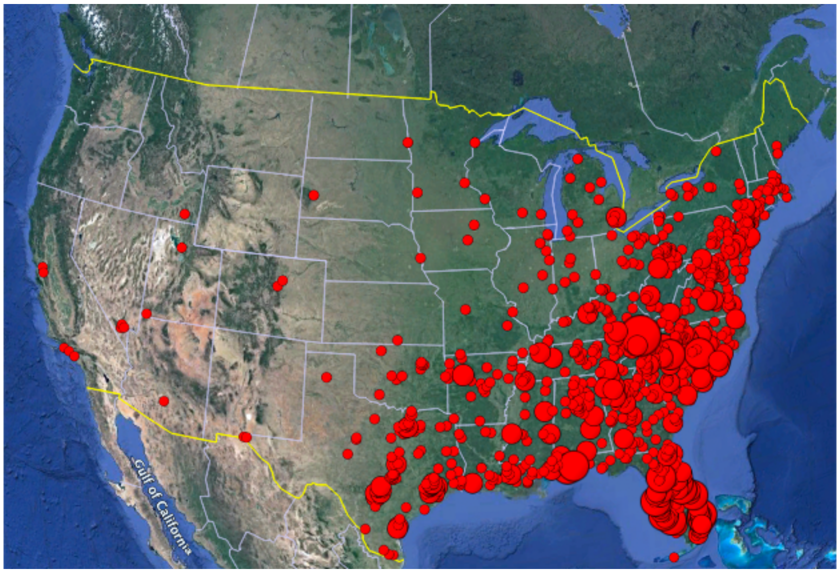
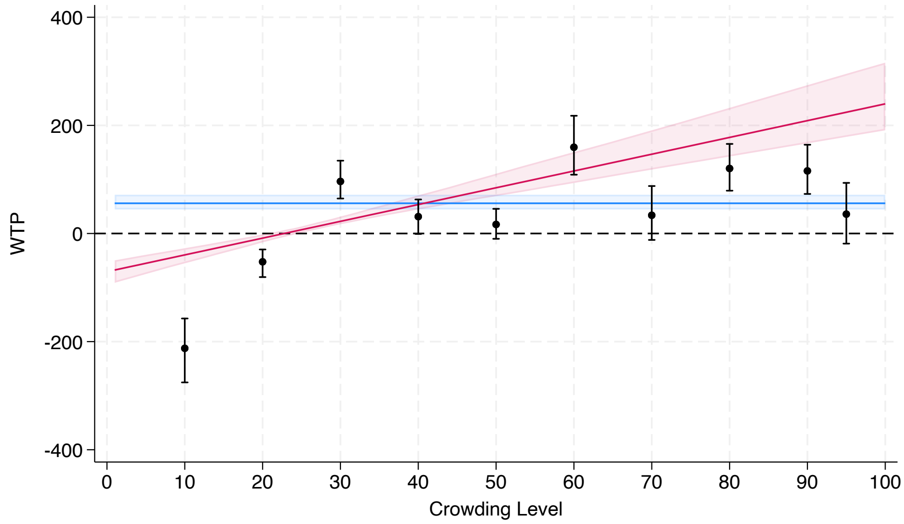
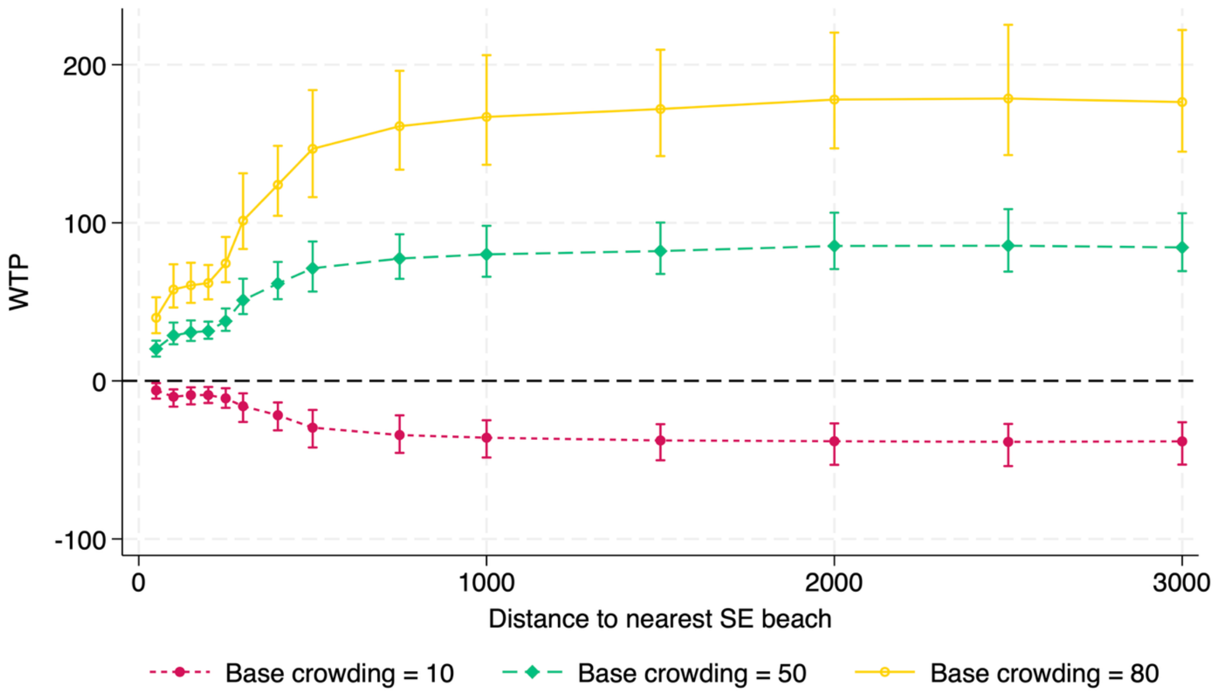


Figure 4: Evidence of nonlinear preferences for crowding



Note: The figure shows how the willingness to pay to reduce crowding by 10 percentage points varies across different crowding levels and models. The figure shows WTP estimates for the linear crowding model (red line), quadratic crowding model (blue line), and semi-parametric crowding model (black dots). Shaded areas and error bars represent 95 percent confidence intervals.

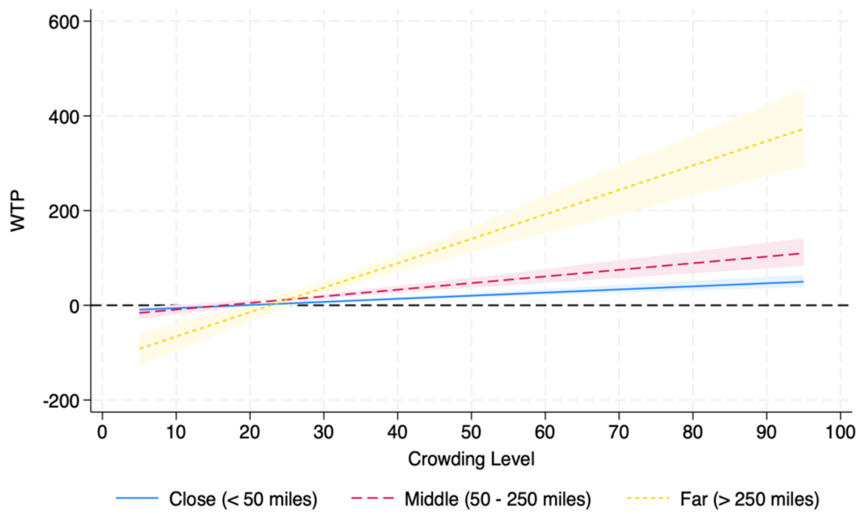
Figure 5: WTP to change crowding by 10 percentage points increases with distance



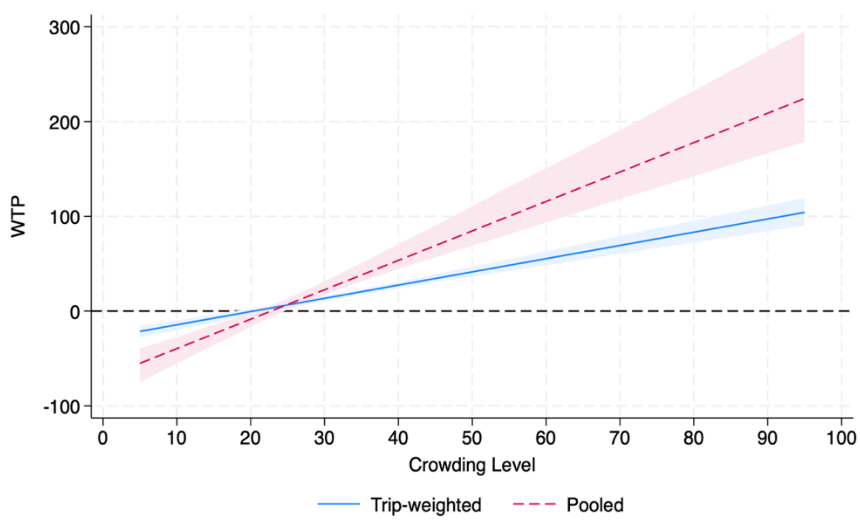
Note: The figure shows how WTP to reduce crowding 10 percentage points varies as the sample expands to include people living farther from a SE beach. For example, the left-most green estimate shows the WTP estimate for the subsample living within 25 miles of a SE beach when the beach is 50 percent crowded. The right-most estimates show WTP for the subsample living within 3,000 miles.

Figure 6: Trip-weighting reduces the magnitude of WTP estimates

(a)



(b)



Note: Panel (a) shows WTP estimates for a 10-percentage point reduction in crowding for the quadratic model from subsamples split by how far a respondent lives from their nearest beach. Panel (b) compares trip-weighted WTP estimates (blue solid line) to WTP estimates from the pooled sample (red dashed line).

Appendix A: Supplemental Figures

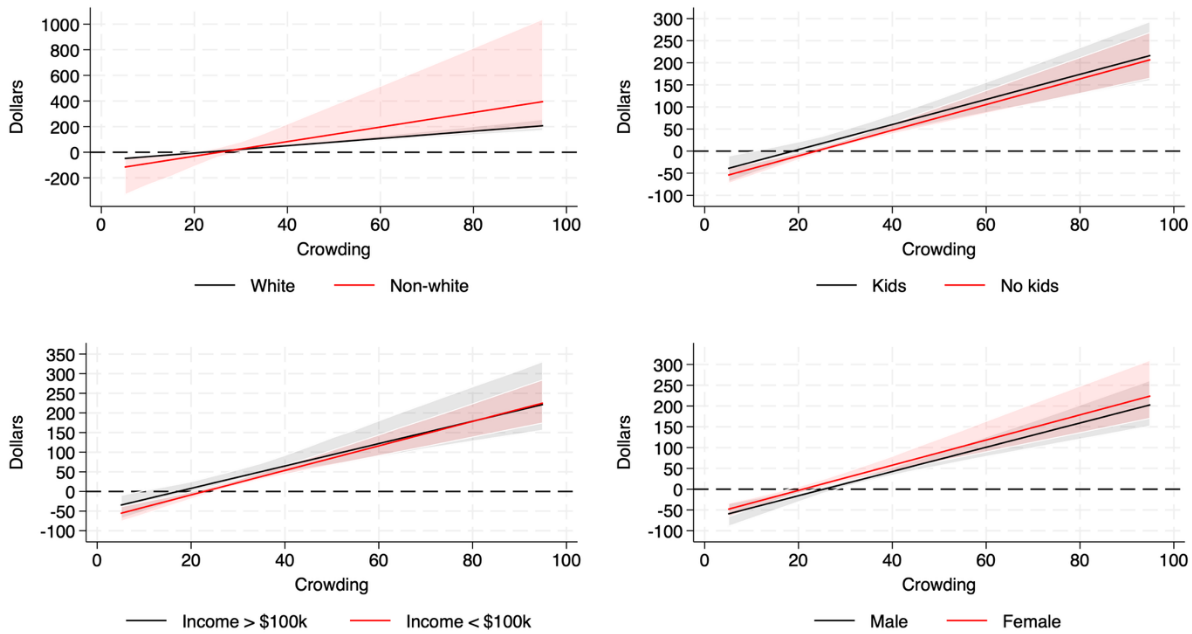
Appendix table A1: Respondent Descriptive Statistics

	Mean (Std. Dev.)	Min	Max
Age	52.348 (16.621)	21.5	75.0
Male	0.320 (0.467)	0.0	1.0
College graduate	0.536 (0.499)	0.0	1.0
Employed full-time	0.390 (0.488)	0.0	1.0
Retired	0.316 (0.465)	0.0	1.0
Household Income	68,776 (49,392)	12,500.0	225,000.0
White	0.834 (0.372)	0.0	1.0
Black	0.113 (0.317)	0.0	1.0
Other race	0.049 (0.217)	0.0	1.0
Hispanic	0.071 (0.258)	0.0	1.0

Appendix table A2: Respondent Preferences

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I do consider crowding when deciding which beach to visit.	6.0	3.8	15.9	33.5	40.7
I would drive farther to recreate at a less crowded beach.	10.0	4.1	23.7	23.0	39.2
I consider a beach's distance from my home when deciding which beach to visit.	3.0	1.8	9.3	50.4	35.6

Figure A1: Heterogeneity in WTP to reduce crowding



Note: The figure shows WTP estimates from the quadratic model for different demographic subsamples. For example, the black line in the top-left panel shows WTP when estimating the model using only white respondents, and the red line shows WTP estimates from the subsample of non-white respondents.