Scale Heterogeneity in Recreationists' Decision Making: Evidence from a Site Choice Model of Sport Fishing

Short title—Scale Heterogeneity in Recreationists' Decision Making

Abstract—Recreation managers and planners recognize the importance of individual preferences and analysts have responded by incorporating individual and group-level heterogeneity in models of recreation behavior. We present a site choice model of recreational fishing that incorporates unobserved heterogeneity through a scale effect. By testing for scale heterogeneity, the model more accurately measures variation in site preferences compared with a conditional logit model, and demonstrates that site quality can affect fishing behavior unevenly across individuals. This result has important implications when using the model to predict fishing behavior and to value site quality and site access. We used the results to simulate the welfare impacts of several hypothetical improvements in fish abundance and find that ignoring scale heterogeneity can lead to inflated economic benefit estimates.

Management implications—The information in this study can be used by fisheries managers to economically substantiate and motivate actions to enhance the benefits of recreational fishing. The analysis demonstrates that diversity of preferences means some anglers choose fishing sites based on information about catch and accessibility, while

others care less about these characteristics. Nevertheless, in general, we find that anglers in the U.S. southwest value increases in bass and walleye abundance as well as state programs to improve public fishing access.

Keywords—Recreation demand; valuation; non-market; fisheries; random utility model

1 Introduction

Site choice models of recreational fishing provide lake, reservoir and fisheries managers useful insights into the demand for fishing. These models are widely used in recreation research because they can measure the influence of fishing quality and other site characteristics on the behavior of anglers (Hunt 2005). In doing so, site choice models can predict changes in fishing pressure across a landscape due to changes in the quality or accessibility of one or more sites. Site choice models are also the preferred methodology to value recreational fisheries; by quantifying the tradeoff between site quality, accessibility and travel costs, researchers and managers can use these models to estimate the economic value of fishing sites and changes in fishing quality.

This paper presents the results of a site choice model of recreational fishing developed from a fall 2014 survey of license-holders in the U.S. state of Oklahoma. Recreational fishing is one of the most popular outdoor activities in Oklahoma, totaling 730 thousand anglers out of a population of about 3.8 million, according to the National Survey of Fishing, Hunting and Wildlife-Associated Recreation (2011). Our work adds to existing research on recreation demand in two ways. First, the model characterizes the locational preferences of anglers in a part of the U.S. Southwest. The insights are therefore likely to be more generalizable to the region than those from more dated studies in other regions. Second, we use the model to examine whether observed site characteristics affect choice behavior in the same way across anglers. This is done by estimating the model as a scale heterogeneity logit, which allows the model to recognize that the site choices of some anglers are attributable to observable site characteristics but

that the choices of others may be influenced relatively more by latent characteristics (Brefle and Morey 2000, Fiebig et al. 2010).

Site choice models are widely used, but the geographical focus of existing applications to anglers is concentrated on fisheries in the northeast United States, the North American Great Lakes, and coastal regions (see the literature reviews in Hunt (2005), Johnston et al. (2006) and Melstrom et al. (2015)). There is a relative paucity of research examining the site choices of anglers living in the North American interior, despite a long history of fisheries management there (Nielsen 1999). Published site choice models of fisheries in this region include Jakus et al. (1997), Jakus et al. (2000) and Parsons et al. (1999), who studied reservoir anglers in Tennessee; Adamowicz (1994) and Peters et al. (1995), who studied stream and lake anglers in Alberta; and Train (1998) and Morey et al. (2002), who studied stream anglers in Montana. Existing models could be used to describe behavior and to value fisheries in regions that currently lack studies, but this is undesirable if the preferences of anglers differ between regions (Johnston et al. (2006) reports several differences). Thus, there is a critical need to learn about the site preferences of anglers in understudied regions like the southwest United States.

Fisheries managers need information about angler heterogeneity, which recreation researchers have tackled by developing models that account for observable and unobservable heterogeneity in fishing preferences. The simplest site choice model is estimated as a conditional logit, which assumes an attribute observed by all decision makers has a homogenous effect on choice. Individual-level heterogeneity can be incorporated into these models by interacting site quality with demographic variables (Brefle and Morey 2000, Hunt 2008). Mixed logit models generalize the conditional

logit to allow for unobserved heterogeneity in the effects of observed attributes. Conditional and mixed logits are widely used in recreation demand modeling (Train 1998, Alvarez et al. 2014). We build on existing work by estimating the site choice model as a scale heterogeneity logit, which generalizes a conditional logit to measure heterogeneity in the stochastic component. By including a scale effect, the model can measure whether observed site quality affects behavior consistently across anglers or, put differently, if site choice is driven more by unobserved attributes (from the analyst's perspective) for some anglers than for others. In comparing the estimates from conditional and scale heterogeneity logits, we find restricting the scale factor to be equivalent across individuals in the conditional logit can lead to significant differences in the predicted value of site quality changes, which can have important implications for managing recreational fishing sites.

2 Scale and taste heterogeneity in choice models

Fishing site choice models are a way of explaining the variety of behaviors observed in a population of anglers. To the analyst, variation in choice can be described by forms of heterogeneity in terms of differing site attributes and angler characteristics. Analysts also regularly distinguish between observable and unobservable heterogeneity, which refer to the influences of observed and unobserved variables, respectively.

Scale heterogeneity is different from taste heterogeneity in choice analysis. With taste heterogeneity, the attributes that describe a choice alternative may be influential to some decision makers but not others. For example, if bass anglers but not trout anglers care about bass catch rates, then there is taste heterogeneity in catch rates. In site choice

modeling, taste heterogeneity allows for sources of variation in the effects of observable site attributes, which in turn may be due to observable or latent characteristics of the decision makers. Continuing with the catch rate example, if the analyst can distinguish between bass and trout anglers in the data, then observed taste heterogeneity in catch rates can be incorporated into the model by fixing the effect of bass catch rates to zero for anglers who do not fish for bass. In contrast, scale heterogeneity refers to variation in the idiosyncratic error of the choice model. The choices of some decision makers may be well explained by the attributes of the alternatives, in which case the model error for them is small, but for others choice may be poorly explained by the observed attributes and for them the error is large. Therefore, scale heterogeneity accounts for the relative influence of the unobservable characteristics as a whole. Note that if there were no scale or taste heterogeneity, then decision makers would be affected identically by all the characteristics that describe a choice alternative. When this is not true, accounting for scale heterogeneity, taste heterogeneity, or both will improve the predictive power of the choice model. Furthermore, measuring scale and taste heterogeneity provides managers information about preference diversity in the population of anglers.

3 Methods

3.1 Site choice model

Based on random utility maximization (RUM) theory, the demand for recreational fishing sites can be characterized by relative differences in site attributes. RUM-based site choice models assume individuals pick the site with the highest utility. For an individual angler

i , let A denote the number of sites in the model and U_{ij} denote the utility level associated with site $j = 1, \dots, A$. The indirect utility from choosing site j can be written as:

$$(1) \quad U_{ij} = x_j\beta + x_jz_i\gamma + p_{ij}\rho + \varepsilon_{ij}/\sigma_i$$

where x_j includes the site attributes that vary across sites and relevant for all anglers, the term x_jz_i interacts site attributes with angler characteristics to measure observable taste heterogeneity, p_{ij} is the travel cost to angler i of fishing at site j , σ_i measure the scale effect specific to angler i and ε_{ij} is idiosyncratic error. The model allows anglers to be different in the importance they place on known site characteristics relative to unknown (from the analyst's perspective) characteristics. An angler whose choice is more influenced by unobserved site quality will have a smaller σ than an angler whose choice is more affected by observed site quality (Brefle and Morey 2000).

Trips are taken to site j where $U_{ij} > U_{ik}$, although the researcher only observes the portion $V_{ij} = x_j\beta + x_jz_i\gamma + p_{ij}\rho$ and out of sample cannot predict with certainty the preferred fishing site for a given trip. Assuming ε_{ij} has mean zero and is distributed extreme value yields the conditional logit model, with the probability of visiting site j

$$(3) \quad \text{prob}_i(\text{choose } j) = e^{\sigma_i V_{ij}} / \sum_{k=1}^A e^{\sigma_i V_{ik}},$$

where it is usually assumed $\sigma_i = 1$ or at least $\sigma_i = \sigma$ so that the error variance is constant across decision makers and the coefficient estimates correspond to $\sigma\beta$, $\sigma\gamma$ and $\sigma\rho$ (Greene 2003). Although it is not possible to identify σ from the other parameters, it plays an important role in the probabilities predicted from the model. As σ approaches zero the error variance approaches infinity and the model predicts equal choice probabilities for all sites (Ben-Akiva and Lerman 1985). In other words, the model is less able to predict deterministically the site with the highest utility when variability in the error is large

relative to the observed component V_{ij} . This result is intuitive. However, ignoring scale heterogeneity in the case $\sigma_i \neq \sigma$ can cause the model to make misleading predictions, similar to how ignoring scale differences in combined choice data can bias coefficient estimates (Swait and Louviere 1993; Whitehead et al. 2008).

The scale heterogeneity logit allows scale to vary across individuals by assuming σ_i is distributed lognormal, which assures the scale is always positive, with mean θ and standard deviation τ (Fiebig et al. 2010). The probability of visiting site j is then

$$(4) \quad \text{prob}_i(\text{choose } j) = \int e^{\sigma_i V_{ij}} / \sum_{k=1}^A e^{\sigma_i V_{ik}} f(\sigma_i | \tau) d\sigma_i.$$

where $f()$ is the lognormal density. Note that this model has gone by different names in the literature, including the random scale logit (Brefle and Morey 2000) and the scale heterogeneity multinomial logit (S-MNL) (Fiebig et al. 2010). While the mean parameter θ is normalized for the purposes of identification, τ can be interpreted as a measure of heterogeneity between anglers. A test of $\tau = 0$ is a test of the assumption of no scale heterogeneity.

The probability function (3) for $\sigma_i = \sigma$ and the probability function (4) for $\sigma_i \neq \sigma$ can be used to form a likelihood function to estimate the parameters by maximum likelihood methods. We use the generalized multinomial logit statistical package (the scale heterogeneity logit is a special case of the generalized multinomial logit) developed by Gu et al. (2013) to estimate the scale heterogeneity logit. The estimation was conducted in STATA and the code is available from the authors upon request.

3.2 Economic valuation

Changes in the quality and accessibility of fishing sites can be valued using the estimates of the site choice model. Monetary values are computed as the maximum amount an angler is willing to pay (WTP) to forgo a change to a fishing location, which is the amount required to equate the utility an angler would get in the altered state to the utility they get in the current state (Wilson and Carpenter 1999). Following Breffle and Morey (2000), WTP is expressed as

$$(5) \quad \text{WTP}_i = \frac{1}{\sigma_i \rho} \left[\ln \left(\sum_{k=1}^A e^{\sigma_i V_{ik}^1} \right) - \ln \left(\sum_{k=1}^A e^{\sigma_i V_{ik}^0} \right) \right]$$

where V^0 denotes utility in the current state and V^1 utility in the altered state. When $\sigma_i = \sigma$ for the conditional logit, equation (5) simplifies to (Haab and McConnell 2003)

$$(6) \quad \text{WTP} = \frac{1}{\rho} \left[\ln \left(\sum_k e^{V^1} \right) - \ln \left(\sum_k e^{V^0} \right) \right].$$

3.3 Data

To parameterize the model we used data from the Oklahoma Recreational Angler Survey conducted by the Oklahoma Department of Wildlife Conservation (ODWC). This survey was administered to a random sample of Oklahoma fishing license holders through a mixed-methodology in fall 2014. All anglers selected for the survey were mailed a pre-survey postcard notification, which allowed anglers to access the survey online using a web link and unique identification number. However, identification numbers were not printed in the correct spot making it difficult for anglers to respond in this manner, so subsequently anglers were mailed a paper questionnaire with instructions for completing the survey either by mail, telephone or internet. License holders who did not respond by mail or online were contacted by telephone after three weeks.

The raw survey response rate was approximately 26% with an adjusted response rate of 45% after excluding invalid phone numbers. 41% responded by mail, 51% by phone and 8% by internet. To assess non-response bias, answers from survey participants for whom the telephone interview was completed after one or two attempts (50% of all telephone respondents) were compared to the responses for those interviewed after three or more attempts (the remaining 50%) for the following variables: fishing participation, education, license type, age, average miles driven and average number of days fished. Mail respondents were not used in the comparison. No significant differences were found for any of the selected variables. Significant differences for some variables were found when we compared differences between response mode; specifically, anglers' age group and satisfaction with the ease of purchasing a fishing license. Research has shown that responses to scalar questions (as was used in the satisfaction question) tend to differ between telephone responses and mail or internet responses, with telephone respondents tending to select the extremes on the scale more often (Dillman et al. 2014). Differences across response modes were not significant for fishing participation, education, license type, average miles driven and average number of days fished. Due to limited evidence of systematic response bias, no sample weighting was done in model estimation.

The survey collected data on a number of variables, but our study relies primarily on information provided about the location of an angler's home and the destination of their most recent fishing trip in Oklahoma. Complete trip information was provided by 536 respondents. Time-of-year bias in the reported trip data is possible because the survey was conducted only in the fall. However, the proportions of black bass and trout anglers in the sample (49% and 8%) are very similar to those from much larger surveys

(56% and 9%; Leonard 2005), and the fishing sites chosen by the sample are largely consistent with anecdotal evidence, with the majority taken to the larger lakes in the northeast and central regions of the state that are known to be popular fishing destinations (for example, Grand Lake and Lake Eufaula).

The set of fishing sites includes all major public lakes in Oklahoma (which are exclusively reservoirs). A database was created using a list maintained by the Oklahoma Water Resources Board (OWRB), a list of ODWC-owned fishable lakes, and any other lakes noted by anglers in the survey as fishing destinations. Excluding lakes that were closed to fishing in 2014, this database counted 147 lakes. Approximately 13% and 18% of the sample went to rivers and private ponds, respectively, which suggests that these sites could be important substitutes for public lakes (Jones and Lupi 1999). To allow potential substitution effects between lakes and other fishable locations, we created two aggregated alternatives, one each for river and pond sites. This made for a total of 149 fishable alternatives in the model.

Travel costs were calculated using information on travel distances, angler characteristics and gasoline prices. Travel distances from the centroid of an angler's home zip code to the centroid of each fishable alternative were estimated using the PC*Miler program (ALK Technologies).¹ Income was measured as the midpoint of an angler's income category from one of six possible categories on the questionnaire or, when anglers omitted a response, the census-reported zip code median income. We then

¹ As pointed out by a reviewer, large zip codes likely induce measurement error in travel costs. This would bias the estimated travel cost coefficient downward and inflate benefit estimates. The majority of our sample live in urban and suburban areas with zip codes of approximately 10 square miles in size. Nevertheless, in rural areas the zip code size can balloon to hundreds of square miles, with the average in Oklahoma about 100 square miles, and it is unclear what affect this variation could have on the model. Note that variation in zip code size is common in the travel cost method-valuation literature (Parsons 2003) and probably warrants further study. To see the implications of measurement error bias in a travel cost study, see footnote 4 in Melstrom (2014).

used one third of an angler's income divided by 2000 to proxy for the opportunity cost of travel time (Melstrom et al. 2015). We calculated a driving cost of \$0.43/mile based on the average per-mile maintenance and depreciation costs for light vehicles in AAA reports (AAA 2014). Finally, travel costs were calculated as the sum of round-trip distance in miles times per mile driving costs, plus the opportunity cost of travel time assuming an average driving speed of 45 miles per hour, plus the lake access fee.

Fishing quality at lakes was measured in terms of expected fish abundance. Using fish abundance as a measure of fishing quality is desirable because abundance is an exogenous measure that can be related to catch rates, but unlike catch rates, does not suffer from reporting bias. Reported catch rates are also likely to be confounded by individual fishing methods and gear, which typically go unmeasured. Furthermore, using abundance makes our results accessible to managers who often stock sites based on increases in the number of fish for specific species. The ODWC provided fish sampling data for select species and Oklahoma lakes dating back to 2005. We focused on the abundance of black bass (*Micropterus salmoides* and *Micropterus dolomieu*), walleye (*Sander vitreus*), catfish (*Siluriformes spp.*) and crappie (*Pomoxis spp.*). The anglers in the sample most often target catfish, crappie and black bass. Walleye are less popular but are still considered a key game fish in the state. The ODWC measures black bass abundance through spring electrofishing counts (numbers of fish) and measures walleye, catfish and crappie abundance through fall gillnetting counts. For each species group expected abundance at individual lakes was calculated using an exponential regression model relating abundance to lake-specific water quality and landscape predictors. Specifically, abundance of species s at site j was modeled as

$$(7) \quad A_{sj} = \exp(q_j \alpha_s + \delta_{sj}) + \omega_{sj}$$

where q_j is a vector of lake characteristics, δ_{sj} is a vector of watershed-specific dummies to control for systematic differences in regional abundance and ω_{sj} is the error. Equation (7) was estimated for each species using nonlinear least squares. Predicted abundance was used as the observed measure except for lakes that lacked catch and water quality data, in which case the mean of predicted abundance was used. To develop measures of targeted abundance, the predicted values were then interacted with indicator variables that equaled one if an angler reported a preference for the species in question and zero otherwise. These interactions were used as measures of fishing quality in the site choice models.

Site characteristics related to accessibility can play an important role in the demand for fishing (Dabrowska et al. 2014). We therefore collected data on shoreline length, the number of public boat ramps, whether the lake is enrolled in the Close to Home fishing program (CTHFP) and whether the lake is operated by the ODWC for public fishing. Following Montgomery and Needelman (1997) and Train (1998), shoreline is expected to proxy for the number of fishable locations around a lake. The ODWC sponsors the CTHFP to improve fishing opportunities and facilities at urban lakes, in addition to operating several rural lakes for the purposes of fishing. Positive coefficients on the physical variables (i.e. the amount of shoreline and boat ramps) and program variables (i.e. the CTHFP and ODWC-operated lakes) in the model would indicate that anglers prefer lakes with more of these characteristics relative to comparable sites. Alternative-specific constants were added to the model for the two aggregated

alternatives for rivers and ponds. Descriptive statistics of the site data used in the model are provided in Table 1.

Finally, we created several interaction variables between site attributes and angler characteristics to measure group-level differences in fishing preferences. The variable for ramps was interacted with a dummy variable for whether an angler prefers to fish from a boat; the pond-specific constant was interacted with dummy variables for whether an angler prefers to fish for black bass and catfish, as these species are commonly stocked in private ponds (Wolinsky 2005); and the river-specific constant was interacted with a dummy variable for trout anglers, as the most popular trout fishing areas in the state are thought to be located at rivers (Fisher et al. 2002). These interaction terms allow the model to control for observable sources of heterogeneity at the group level.

Table 1. Descriptive statistics of the site attributes used in the site choice model (N = 149)

Variable	Description	Mean	St. Dev.
<i>Shoreline</i>	Natural log of shoreline length in miles	2.464	1.486
<i>CTHFP</i>	Dummy = 1 if lake is part of the state's Close to Home fishing program	0.020	0.141
<i>ODWCL</i>	Dummy = 1 if lake is maintained by the ODWC specifically for public fishing	0.087	0.283
<i>Ramps</i>	Number of boat ramps at lake	3.221	7.209
<i>Black bass</i>	Predicted abundance based on electrofishing survey data	67.598	31.437
<i>Walleye</i>	Predicted abundance based on gillnetting survey data	0.143	0.285
<i>Catfish</i>	Predicted abundance based on gillnetting survey data	2.893	2.467
<i>Crappie</i>	Predicted abundance based on gillnetting survey data	1.784	1.496
<i>Pond</i>	Dummy = 1 for pond aggregated alternative	0.007	0.082
<i>River</i>	Dummy = 1 for river aggregated alternative	0.007	0.082

4 Results

4.1 Site choice models

Table 2 presents the coefficients of the conditional and scale heterogeneity logit models. Parameters are not directly comparable across logit models because σ is unidentified, but in general the two models feature coefficients that share the same directional signs, magnitudes and measures of statistical significance. In the next section we compute the welfare effects of several site quality changes, which convert the results from the two models into comparable units.

The travel cost coefficient has the expected negative sign and is statistically significant at the 0.05 level in both models, indicating that the probability of a trip to a site is decreasing in the trip price. The models estimate a positive coefficient on shoreline length, so the probability of a trip to a particular lake increases with the size of the lake. Likewise, both models estimate positive effects for the CTHFP and ODWC-operated lakes, although only the former is statistically significant, at the 0.05 level. The effect of boat ramps on general anglers is not significantly different from zero in either model.

The effect of fish abundance on site choice is mostly positive, implying that the probability of visiting a site increases with expected abundance. However, only the coefficients for the targeted bass and walleye measures are statistically significant, at the 0.05 level in both models except for targeted bass in the scale heterogeneity logit model which is significant at the 0.10 level. The coefficient on targeted catfish abundance is a fairly precise zero in the conditional logit model and negative in the scale heterogeneity logit, suggesting that catfish abundance plays little role in site choice. The coefficient on crappie is consistently positive in both models, but imprecisely estimated. This evidence

supports the interpretation that abundance matters to bass and walleye anglers, but may be less important to catfish and crappie anglers.

Table 1: Results of the conditional and scale heterogeneity logit models

Variable	Conditional Logit		Scale Heterogeneity Logit	
	Coef.	St. Err.	Coef.	St. Err.
<i>Travel cost</i>	-0.017**	0.001	-0.026**	0.003
<i>Shoreline</i>	0.931**	0.044	1.080**	0.077
<i>CTHFP</i>	1.820**	0.607	1.863**	0.899
<i>ODWCL</i>	0.760	0.522	0.454	0.887
<i>Ramps</i>	-0.002	0.005	-0.010	0.008
<i>Ramps × boat user</i>	0.027**	0.005	0.046**	0.011
<i>Black bass × bass angler</i>	0.005**	0.002	0.004*	0.002
<i>Walleye × walleye angler</i>	1.204**	0.276	1.530**	0.311
<i>Catfish × catfish angler</i>	0.000	0.027	-0.009	0.033
<i>Crappie × crappie angler</i>	0.025	0.055	0.008	0.068
<i>River</i>	3.789**	0.262	3.778**	0.349
<i>River × trout angler</i>	1.907**	0.344	1.891**	0.405
<i>Pond</i>	3.135**	0.403	3.224**	0.482
<i>Pond × bass angler</i>	2.012**	0.333	2.020**	0.363
<i>Pond × catfish angler</i>	-0.030	0.265	-0.152	0.303
τ (scale deviation)	0.000 ^a		0.620**	0.089
Trips (<i>N</i>)		536		536
Log-likelihood		-1493.916		-1471.504

* Significant at the 0.10 level. ** Significant at the 0.05 level.

^aScale (σ) is normalized to 1 so $\tau = 0$.

Several of the interaction variables are found to be relevant in the site choice decision. The effect of boat ramps for anglers who typically fish from a boat is positive and statistically significant at the 0.05 level in both models, indicating that the probability

of a trip to a lake increases with the number of boat ramps if the angler uses a boat. The coefficient on the interaction between the river alternative and trout anglers is positive and statistically significant at the 0.05 level, which confirms that trout anglers do disproportionately fish at rivers. Similarly, the coefficient on the interaction between the pond alternative and bass anglers is positive and statistically significant at the 0.05 level, which shows bass anglers are more likely to fish at ponds than non-bass anglers. The interaction between the pond alternative and catfish anglers is not statistically significant.

Including the individual scale effect improves the model fit significantly.² The estimated deviation parameter (τ) is significantly different from zero at the 0.05 level, providing evidence of scale heterogeneity. This implies that for some anglers the observed site characteristics do a good job of characterizing preferences (hence the scale effect for them is large), while for other anglers site choice is driven more by unobserved factors (so the scale effect for them is small).

4.2 Economic valuation

WTP is computed for each trip in the sample using the estimated parameters, individual characteristics and site quality measures in the current state V_j^0 relative to the hypothetical site quality measures for V_j^1 , the proposed future state.³ This allows each individual to have their own WTP estimate and thus incorporates the observed heterogeneity. To demonstrate the capabilities of the model, below we report the sample

² Using a likelihood-ratio test, we easily reject the hypothesis of no improvement, with a ratio statistic of 44.82 compared with a critical value of 3.84 for a significance level of 0.05 and one degree of freedom.

³ We construct the current-state and proposed-state utility functions explicitly in Stata and calculate WTP using the formula in section 3.2. However, for the special case of an equal quality change across all sites, a simplified expression is obtain where $WTP = \beta/\rho$ where β is the vector of parameters associated with the changed quality attributes (Haab and McConnell 2002), which can be easily implemented in Stata using the `nlcom` command after estimating the model.

average WTP for six hypothetical but plausible policies involving changes in fishing quality. The first set of policies measures the benefits arising from a 50% increase in black bass abundance at certain lakes in Oklahoma. The second set of policies changes the extent of two fishery access programs, including the CTHFP program and a collection of rural reservoirs managed by Oklahoma's state wildlife department. In the first set of policies, we present WTP as loss-to-trip ratios by evaluating equation (5) and dividing by the average probability that a trip is taken to the affected site (Parsons et al. 2009). Loss-to-trip ratios are interpreted as the monetary value to those fishing trips taken specifically to the affected site. The remaining WTPs are calculated as in equation (5), and are interpreted as the monetary value to each fishing trip in the state.

Using the parameter estimates we calculate the economic value of a 50% increase in black bass abundance first at Grand Lake, then at Lake Raymond Gary and finally at all reservoirs in the state. These estimates are reported in the first three rows of Table 3. Grand Lake is one of the largest lakes in Oklahoma and a popular bass fishery. Lake Raymond Gary is more typical of medium-sized lakes. When using the coefficients from the conditional logit model, a 50% increase in bass at Grand Lake is worth around \$8/trip for trips to Grand Lake while a 50% increase at Lake Raymond Gary is worth around \$6/trip for trips to Lake Raymond Gary. The average WTP for the same increase at every lake is \$4.35/trip.

Anglers are willing to pay to avoid ending urban fishing programs, to avoid closing sites and to open new sites. When using the coefficients from the conditional logit model, eliminating the CTHFP (but not eliminating access to the lakes associated with the program) would result in an average loss of \$0.28/trip, while closing (and eliminating

access to) the ODWC-operated lakes would result in an average loss of \$0.56/trip. We also estimate that the value of reopening American Horse Lake, a lake that was closed in 2014 due to a combination of dam repairs and low water levels, is worth on average \$0.15/trip to Oklahoma anglers.

The welfare estimates are notably different when the model controls for scale heterogeneity. WTP is consistently smaller (in absolute value) when calculated using the coefficients from the scale heterogeneity logit. We tested for statistically significant differences between the WTP estimates using the procedure described in Poe (2005). We found WTP from the scale heterogeneity logit was significantly smaller (at the 0.05 level) in five out of the six policies. Only WTP for the ODWC lakes was not statistically different between the scale heterogeneity and conditional logit models. Across all policies, the proportional difference in WTP ranged from 19% to 79% (see Table 3). For example, when measuring the benefits of black bass, WTP from the conditional logit is more than twice as large as WTP from the scale heterogeneity logit; the range in WTP from the conditional logit is also relatively small compared to the scale heterogeneity logit, which is an effect of the latter model allowing for a wider range of individual behavior. This suggests that controlling for scale heterogeneity in decision making is important in terms of individual-level predictions as well as simulating the economic welfare effects of changes in site quality.

Table 3. Mean per trip WTP (\$) for changes in select site attributes

Policy	Conditional Logit		Scale Heterogeneity Logit	
	Mean WTP	90% CI ^a	Mean WTP	90% CI ^a
50% increase in black bass at Grand Lake ^b	8.03	(3.31, 12.27)	3.22	(0.21, 7.71)
50% increase in black bass at Lake Raymond Gary ^b	6.04	(2.21, 9.46)	1.16	(0.00, 3.13)
50% increase in black bass at all lakes in Oklahoma	4.35	(1.86, 7.19)	1.92	(0.11, 4.62)
Eliminate Close to Home fishing program	-0.28	(-0.63, -0.04)	-0.22	(-0.62, 0.05)
Close ODWC-operated lakes	-0.56	(-1.08, -0.14)	-0.39	(-0.91, -0.08)
Re-open American Horse Lake ^c	0.15	(0.03, 0.23)	0.07	(0.02, 0.15)

^aCalculated using the bootstrapping method.

^bWTP is denominated per trip for fishing trips to the lake in question.

^cThe conditional logit model predicts 0.21% of state resident fishing trips would go to American Horse Lake if it were re-opened, while the scale heterogeneity logit predicts 0.16%.

5 Discussion

The analysis in section 4 shows that scale heterogeneity can play an important role in modeling recreationists' decision making. By significantly improving the fit of the model, the estimated scale effect indicates that site choice is explained relatively well by the observed variables for a subgroup of anglers. This result means that for some anglers the modeled attributes are important for decision making, while for other anglers these attributes matter little and so their behavior appears to be driven by other factors (Fiebeg et al. 2010). These other factors could include the abundance of other species, proximity to a fishing companion's home and place attachment. In the extreme, there may be anglers who attach no importance to the site attributes in the model.⁴

While both models are in general agreement about the site characteristics that matter to most anglers, there are notable differences in the economic welfare effects they predict. The value of site quality appears to be overstated when scale heterogeneity is ignored, which is concerning because the conditional logit is the traditional model in valuing recreational resources. Because this research is one of the first to confirm evidence of scale heterogeneity in a recreation demand setting, it is not clear if this result may be part of a general pattern. To our knowledge, only Breffle and Morey (2000) develop a similar model with scale heterogeneity. The scale deviation parameter in their model is 0.64, which lies very near our estimate of 0.62. Breffle and Morey also find that

⁴ Future research could relate this choice behavior (that is, the size of the scale effect) to individual characteristics such as trip avidity, skill and motivation, and whether the angles prefers to fish with family or friends. Existing research suggests that the perceived substitutability of fishing sites for anglers is related to fishing specialization (Oh et al. 2013).

WTP is greater when calculated using the coefficients from a conditional logit compared with a scale heterogeneity logit.

While a large amount of research documents the existence of unobserved heterogeneity in individual coefficients—that is, whether some anglers care more about particular attributes than others—the scale heterogeneity logit assumes all sources of taste heterogeneity are observed. This limitation could be addressed by using a mixed logit to model site choice, or a generalized multinomial logit, which nests scale and mixed logits (Fiebig et al. 2010). However, applications of mixed and general multinomial logits typically involve thousands of observations with several observations per individual, while there are 536 trips with one trip per angler in the sample used in this study. Random coefficients may be very poorly identified when estimated with limited cross section data (Berry et al. 1995; Harris and Keane 1999) and small sample sizes (Chang and Lusk 2011), a fact born out in trial applications to the Oklahoma data not reported here. In other words, there may be important sources of unobserved taste heterogeneity but our sample size is too small to support models that would seek out those sources. In contrast, despite the small sample the effect of scale is precisely measure.

In regards to the coefficients presented in this paper, the model implies that abundance is important to the site choice behavior of black bass and walleye anglers' but not catfish or crappie anglers. This contrasts with published evidence that panfish (which include crappie) abundance influences site choice in the U.S. Great Lakes region (Melstrom et al. 2015). Possibly, crappie anglers in the U.S. southwest are less motivated by abundance than they are by other harvest characteristics, such as fish size. This explanation may also be true for catfish anglers and is supported by other research on

Oklahoma fishing (Mahasuweerachai et al. 2010). It is also possible that the coefficients are biased due to the quality of the abundance data. We relied on measures of abundance reported from fish sampling, which showed considerable variability between lakes and even within lakes that were repeatedly sampled. While the fish sampling data has the advantage of not relying on angler-reported catch, for some sites the predictions may be imprecise.

6 Conclusion

Recreational anglers can and do respond in different ways to known measures of site quality. Using a scale heterogeneity logit, we found significant differences in the influence of observed site quality on the choice of where to fish, demonstrating that for some anglers travel costs, catch rates and lake size matter in where they go fishing, while for other anglers site choice is driven relatively more by unobserved factors.

Our analysis demonstrates that incorporating scale heterogeneity can significantly improve the fit of site choice models. Previous recreation demand studies using site choice models have ignored scale heterogeneity, despite widespread recognition that individual heterogeneity is an important facet in choice behavior. Accounting for scale heterogeneity may be particularly important in cases where modeling unobserved taste heterogeneity is not possible. There are two benefits from relaxing the assumption of no scale effects. First, doing so allows the analyst to model a wider range of individual behavior, including choices that the observed attributes cannot explain well. This type of information may be useful in managing recreation demand; for example, advertising recreational opportunities is likely to be more effective if aimed at decision makers

whose preferences are known. Second, in every hypothetical policy we examined, welfare estimates became inflated when scale heterogeneity was ignored.

The results from the application can be used by managers and policy makers to make informed decisions about protecting fishing quality. We showed that black bass and walleye are two of the more important and valuable fish species in Oklahoma, and that fishing access programs sponsored by the state wildlife agency matter to anglers. Furthermore, the economic values reported in the paper can be used to measure the annual benefits of several policies by multiplying the per trip values by the affected number of trips taken in a year. For example, we found that on average anglers are willing to pay about \$0.22 (USD, 2014) per trip to maintain the Close to Home urban fishing program, holding other quality measures fixed. This value is averaged across all trips in the state, so the annual value of the program is measured by multiplying the per-trip value by the total number of trips in a year. Continuing with the example, with 7,449,000 fishing trips taken in Oklahoma by residents in 2011 according to the National Survey of Fishing, Hunting and Wildlife Associated Recreation (US Fish and Wildlife Service, 2014), our estimate implies an annual benefit of the Close to Home fishing program of over \$1.6 million (USD, 2014). Although there are no available estimates of this program's cost, the annual benefit compares favorably with the \$2 million per year value of the Lower Illinois River trout fishery in Oklahoma, which does pass the cost-benefit test (Prado 2006). We anticipate that the results presented in this paper will be useful for predicting demand and carrying out benefits transfer to other recreational fisheries in the region.

Acknowledgements

The authors thank Kurt Kuklinski and John Polo for providing the abundance and landscape data used in the analysis. Financial support was provided by the Oklahoma Agricultural Experiment Station and NSF EPSCoR (Grant No. OIA-1301789).

References

- AAA. *Your Driving Costs*. (2014). Available at: <http://publicaffairsresources.aaa.biz/wp-content/uploads/2014/05/Your-Driving-Costs-2014.pdf> (accessed April 22, 2015).
- Adamowicz, W., Louviere, J., & Williams, M. (1994). Combining revealed and stated preference methods for valuing environmental amenities. *Journal of Environmental Economics and Management*, 26(3), 271-292.
- ALK Technologies. (2012). PC Miler, Version 27, ALK Technologies, Inc., Princeton, New Jersey.
- Alvarez, S., Larkin, S. L., Whitehead, J. C., & Haab, T. (2014). A revealed preference approach to valuing non-market recreational fishing losses from the Deepwater Horizon oil spill. *Journal of Environmental Management*, 145, 199-209.
- Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press.
- Berry, S., Levinson, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63(4): 841-890.
- Breffe, W. S., & Morey, E. R. (2000). Investigating preference heterogeneity in a repeated discrete-choice recreation demand model of Atlantic salmon fishing. *Marine Resource Economics*, 15(1), 1-20.
- Chang, J. B., & Lusk, J. L. (2011). Mixed logit models: accuracy and software choice. *Journal of Applied Econometrics*, 26(1), 167-172.
- Dabrowska, K., Haider, W., & Hunt, L. (2014). Examining the impact of fisheries resources and quality on licence sales. *Journal of Outdoor Recreation and Tourism*, 5, 58-67.
- Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method*. New Jersey: John Wiley & Sons.
- Fiebig, D. G., Keane, M. P., Louviere, J., & Wasi, N. (2010). The generalized multinomial logit model: accounting for scale and coefficient heterogeneity. *Marketing Science*, 29(3), 393-421.
- Fisher, W. L. (2015). Recreational fishing and socioeconomic characteristics of eastern Oklahoma stream anglers. In *Proceedings of the Oklahoma Academy of Science*, 82, 79-87.
- Greene, W. H. (2003). Models for Discrete Choice. Chap. 21 in *Econometric Analysis*, by W. H. Greene, 663-752. New Delhi: Dorling Kindersley.
- Gu, Y., Hole, A. R. & Knox, S. (2013). Fitting the generalized multinomial logit model in Stata. *The Stata Journal*, 13(2), 382-397.
- Haab, T. C., & McConnell, K. E. 2003. *Valuing Environmental and Natural Resources. The Economics of Non-market Valuation*. Northampton: Edward Elgar Publishing.

- Hunt, L. M. (2005). Recreational fishing site choice models: Insights and future opportunities. *Human Dimensions of Wildlife*, 10(3), 153-172.
- Hunt, L. M. (2008). Examining state dependence and place attachment within a recreational fishing site choice model. *Journal of Leisure Research*, 40(1), 110.
- Jakus, P. M., Downing, M., Bevelhimer, M. S., & Fly, J. M. (1997). Do sportfish consumption advisories affect reservoir anglers' site choice? *Agricultural and Resource Economics Review*, 26, 196-204.
- Jakus, P. M., Dowell, P., & Murray, M. N. (2000). The effect of fluctuating water levels on reservoir fishing. *Journal of Agricultural and Resource Economics*, 25(2), 520-532.
- Johnston, R. J., Ranson, M. H., Besedin, E. Y., & Helm, E. C. (2006). What determines willingness to pay per fish? A meta-analysis of recreational fishing values. *Marine Resource Economics*, 21(1), 1-32.
- Jones, C. A., & Lupi, F. (1999). The effect of modeling substitute activities on recreational benefit estimates. *Marine Resource Economics*, 14(4), 357-374.
- Leonard, J. (2005). Black bass and trout fishing the United States. Addendum to the 2001 national survey of fishing, hunting, and wildlife-associated recreation, U.S. Fish and Wildlife Service Report 2001-10, Arlington, Virginia.
- Mahasuweerachai, P., Boyer, T. A., Balsman, D. M., & Shoup, D. E. (2010). Estimating demand for urban fisheries management: an illustration of conjoint analysis as a tool for fisheries managers. *North American Journal of Fisheries Management*, 30(5), 1339-1351.
- Melstrom, R. T. (2014). Valuing historic battlefields: an application of the travel cost method to three American Civil War battlefields. *Journal of Cultural Economics*, 38(3), 223-236.
- Melstrom, R. T., Lupi, F., Esselman, P. C., & Stevenson, R. J. (2015). Valuing recreational fishing quality at rivers and streams. *Water Resources Research*, 51(1), 140-150.
- Montgomery, M., & Needelman, M. (1997). The welfare effects of toxic contamination in freshwater fish. *Land Economics* 73(2), 211-223.
- Morey, E. R., Breffle, W. S., Rowe, R. D., & Waldman, D. M. (2002). Estimating recreational trout fishing damages in Montana's Clark Fork River basin: summary of a natural resource damage assessment. *Journal of Environmental Management*, 66(2), 159-170.
- Nielsen, L. A. (1999). History of inland fisheries management in North America. *Inland Fisheries Management in North America*, 2nd edition. American Fisheries Society: Bethesda, Maryland.
- Oh, C. O., Sutton, S. G., & Sorice, M. G. (2013). Assessing the role of recreation specialization in fishing site substitution. *Leisure Sciences*, 35(3), 256-272.

- Parsons, G. R., Jakus, P. M., & Tomasi, T. (1999). A comparison of welfare estimates from four models for linking seasonal recreational trips to multinomial logit models of site choice. *Journal of Environmental Economics and Management*, 38(2), 143-157.
- Parsons, G. R. (2003). The travel cost model. Chapter 9 in Champ, P. A., Boyle, K. J., & Brown, T. C. (Eds.), *A Primer on Nonmarket Valuation*. Netherlands: Springer.
- Parsons, G. R., Kang, A. K., Leggett, C. G., & Boyle, K. J. (2009). Valuing beach closures on the Padre Island National Seashore. *Marine Resource Economics*, 24(3), 213-235.
- Peters, T., Adamowicz, W. L., & Boxall, P. C. (1995). Influence of choice set considerations in modeling the benefits from improved water quality. *Water Resources Research*, 31(7), 1781-1787.
- Poe, G. L., Giraud, K. L., & Loomis, J. B. (2005). Computational methods for measuring the difference of empirical distributions. *American Journal of Agricultural Economics*, 87(2), 353-365.
- Prado, B. E. (2006). *Economic valuation of the lower Illinois trout fishery in Oklahoma under current and hypothetical management plans*. Doctoral dissertation, Oklahoma State University.
- Swait, J., & Louviere, J. (1993). The role of the scale parameter in the estimation and comparison of multinomial logit models. *Journal of Marketing Research*, 30(3), 305-314.
- Train, K. E. (1998). Recreation demand models with taste differences over people. *Land Economics*, 74(2), 230-239.
- U.S. Fish and Wildlife Service (2014). *2011 Oklahoma National Survey of Fishing, Hunting, and Wildlife-Associated Recreation*. U.S. Fish and Wildlife Service and U.S. Census Bureau.
- Whitehead, J. C., Pattanayak, S. K., Van Houtven, G. L., & Gelso, B. R. (2008). Combining revealed and stated preference data to estimate the nonmarket value of ecological services: an assessment of the state of the science. *Journal of Economic Surveys*, 22(5), 872-908.
- Wilson, M. A., & Carpenter, S. R. (1999). Economic valuation of freshwater ecosystem services in the United States: 1971-1997. *Ecological Applications*, 9(3), 772-783.
- Wolinsky, S. (2005). Farm Pond Ecosystems. *Fish and Wildlife Habitat Management Leaflet*, 29. U.S. Department of Agriculture Natural Resources Conservation Service and Wildlife Habitat Council.