6. Corner Solution Models of Recreation Demand: A Comparison of Competing Frameworks[1]

Joseph A. Herriges, Catherine L. Kling, and Daniel J. Phaneuf

6.1 INTRODUCTION

There is a rich history of recreation demand models estimated using household level data on the number of visits to multiple recreation sites and the travel costs associated with each visit. Over the last 40 years, the state of the art in these models has evolved from fairly simple systems of demand equations to econometrically and theoretically sophisticated variants of the discrete choice models pioneered by McFadden. While the applications themselves have varied greatly, they have shared the common challenge of how to deal with the prevalent occurrence of corner solutions; i.e., the fact that while many recreationists use more than one site, they typically choose not to visit some sites while making multiple visits to others. The presence of these corners has provided a challenge to analysts in terms of specifying both the underlying behavioral model used to explain recreationists' choices and the econometrics of recreation demand.

In this paper, we compare and contrast two state-of-the-art approaches to modeling multiple site recreation demand: the linked site selection and participation model and the Kuhn-Tucker model.[2]

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[1] Forthcoming in Herriges, J. A. , and C. L. Kling (eds.) (1998), *Valuing the Environment Using Recreation Demand Models*, Aldershot: Edward Elgar. The authors would like to thank Kerry Smith for helpful comments on an earlier draft of this chapter.

The linked model was originally developed by Bockstael, Hanemann, and Strand (1986) and Bockstael, Hanemann, and Kling (1987) (hereafter BHK), but has received considerable attention in recent years, with modifications by Hausman, Leonard, and McFadden (1995) (HLM), Feather, Hellerstein, and Tomasi (1995) (FHT), and Parsons and Kealy (1995) (PK), as well as several contributions in this volume (Train; Chen, Lupi, and Hoehn). The Kuhn-Tucker model, on the other hand, is a relative newcomer to the recreation demand arena. We provide a brief description of each approach and assess their relative strengths and weaknesses. Variants of each model are then estimated using a data set on angling in the Wisconsin Great Lakes region.

The purpose of this exercise is not to identify one approach as the best, but rather to discuss the relative theoretical and conceptual merits of the alternative approaches and to compare and assess how each model performs on a common data set. In this sense, we are interested in how well the models fit the underlying data and what welfare estimates they generate for common changes in site prices and/or quality characteristics. If the welfare estimates resulting from these models are similar, we can be more confident that decisions about model choice will not generate widely divergent welfare estimates. On the other hand, if the models generate significantly different point estimates of welfare change, the analyst's model choice takes on greater significance.

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[2] A third approach for dealing corner solutions is the repeated nested logit model developed by Morey, *et al.* (1993). We provide a brief discussion of this model in Section 9.2, contrasting it with the linked site selection/participation and Kuhn-Tucker frameworks. However, due to space constraints, we do not provide an empirical example. See Morey, *et al.* (1995) for a more extensive discussion of the repeated nested logit model as well as the general corner solutions problem.

6.2 THE COMPETING FRAMEWORKS

This section provides a brief overview of both the linked and Kuhn-Tucker models, as well as the repeated nested logit model developed by Morey, *et al.* (1993). In the final subsection, we briefly mention alternative models that can handle corner solutions.

6.2.1 THE LINKED MODEL

Models of this genre have their roots in discrete choice analysis of consumer selection of a single good from among a finite set of alternatives, such as the choice of transportation mode or housing type. In these single choice settings, researchers have generally relied upon the familiar multinomial logit (MNL) or nested logit (NL) specifications. Beyond yielding convenient likelihood functions for estimation, logit models are often justified on the basis of their consistency with McFadden's (1981) hypothesis of random utility maximization (RUM). The RUM hypothesis conjectures that individual agents choose from among the available alternatives in order to maximize their utility and that the distribution of choices made in the population is a reflection, in part, of the distribution of individual preferences. Given certain assumptions regarding this distribution of preferences, the MNL or NL specifications result.[3]

The strong utility theoretic foundation of RUM models have made them a natural choice in modeling site selection in the recreation demand literature. However, site selection models alone capture only one aspect of the recreation demand problem and an important addition to RUM models has been necessary to make them applicable to most recreation demand data sets. In

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[3] Consistency with the RUM hypothesis holds globally for the MNL specification, but requires additional restrictions in the case of NL. See McFadden (1981), Börsch-Supan (1990), and Herriges and Kling (1996) for additional discussion. The multinomial probit (MNP) provides an alternative RUM model, but has received relatively little attention until recently due to the difficulties associated with its estimation.

particular, rather than choosing a single alternative from among a set of alternatives, recreationists face a number of choice occasions over which they may be observed to choose different sites. Thus, there is both a discrete component to the recreationist's decision (which site to visit on a given choice occasion) and a continuous choice (how many trips to take in a season). Recreation demand analysts have therefore adapted the discrete choice models by identifying and linking together these two distinct components of the consumer's recreation decision. In one component, an aggregate demand for the total number of trips recreationists take in a season is modeled (BHK refer to this as the macro-allocation decision, while HLM refer to this as the first stage in their model). A second component entails the estimation of a site selection model. In this component, the recreationist's choice among the available sites on each choice occasion is modeled (BHK term this the micro-allocation decisions, while HLM consider this the second stage in a two-stage budgeting process). This second component is simply an implementation of a standard discrete choice model.

One of the first analysts to see the value of RUM models in recreation demand applications was Hanemann (1978). Other early applications included Feenburg and Mills (1980) and Caulkins, Bishop, and Bouwes (1986). However, it was not until the work of Bockstael, Hanemann, and Kling (1987) that the first component of the model was added to the site selection model to provide a more complete picture of recreationist's behavior. Creel and Loomis (1992), Bockstael, McConnell, and Strand (1989), Hausman, Leonard, and McFadden (1995), and Feather, Hellerstein, and Tomasi (1995), among others, have all followed in this tradition, although there have been important differences in how they link the two components of the models and how they compute welfare estimates from the model parameter estimates.[4] These differences are discussed in

[4] See the introductory chapter of this volume for a more complete literature survey of the related discrete choice models.

detail following the development of the standard linked model structure, beginning with the site selection component.

As noted earlier, the site selection component of the linked model generally begins with the specification of a discrete choice RUM model. The utility that an individual receives from choosing to visit site *j* (*j* = 1, …, J) on a given choice occasion is assumed to take the form of the conditional indirect utility function[5]

$$U_j = V_j + \varepsilon_j \qquad (1)$$

where

$$V_j = V_j(y - p_j, \mathbf{q}_j) \qquad (2)$$

denotes the non-stochastic portion of consumer's utility, y is the per-choice occasion income, p_j is the cost of visiting site *j*, and $\mathbf{q}_j = (q_{j1}, \ldots, q_{jK})'$ is vector of *K* site attributes (e.g., fishing catch rates). The error term ε_j captures the variation in preferences among individuals in the population. On any given choice occasion, the consumer is assumed to visit the recreation site that yields the greatest utility, so that the probability that site *j* is chosen is given by

$$\pi_j = \text{Prob}\left(V_j + \varepsilon_j > V_k + \varepsilon_k \quad \forall\, k \neq j\right). \qquad (3)$$

By specifying the distribution of the error vector $\varepsilon \equiv (\varepsilon_1, \ldots, \varepsilon_J)'$, different standard site selection models result. For example, if the ε_j's are i.i.d. extreme value variates, the MNL model

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[5] The indirect utility function is *conditional* on the alternative chosen. In general, the J alternatives facing an individual on a given choice occasion may include not only which site to visit, but also what type of activity to undertake at that site (e.g., shore fishing versus boat fishing). For simplicity, in this discussion, we treat sites and alternatives as synonymous.

results, whereas with ε drawn from a generalized extreme value (GEV) distribution the NL model results. Alternatively, if the ε's are drawn from a multivariate normal distribution, the MNP results. In what follows, we adopt a nested logit formulation since it and the multinomial logit have accounted for the vast majority of applications and the nested formulation provides a means for relaxation of the independence of irrelevant alternatives assumption.

The nested logit model of site selection requires that the analyst group the available set of alternatives into *nests* of similar sites. Thus, alternatives within the same nest are assumed to be better substitutes for each other than alternatives in different nests. The site selection probability in equation (3) can then be expressed as (McFadden; Maddala; Morey)

$$\pi_j = \frac{e^{V_j/\theta_{n(j)}}\left[\sum_{i \ni n(i)=n(j)} e^{V_i/\theta_{n(j)}}\right]^{(\theta_{n(j)}-1)}}{\sum_{m=1}^{N}\left[\sum_{k \ni n(k)=m} e^{V_k/\theta_m}\right]^{\theta_m}}, \qquad (4)$$

where $n(j)$ is an index function that equals *m* (*m*=1,…, N) if site *j* has been assigned to nest *m* by the analyst, *N* denotes the total number of nests, and θ_m (*m*=1,…, N) is a parameter (known as the dissimilarity coefficient for nest *m*) that measures the degree of similarity of sites within the nest.[6] Once a specific functional form for the utility function is specified, simultaneous estimation of the coefficients can be accomplished by maximizing the log of the likelihood function, defined as the product over the sample of the log of the probabilities from (4).

A useful construct from the site selection model is the inclusive value, defined as

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[6] The parameter θ_m is known as the *dissimilarity* coefficient since the smaller it gets, the more similar are the alternatives within the nest when compared to alternatives outside of the nest. Global consistency with the RUM hypothesis requires that θ_m lie in the unit interval, with $\theta_m = 1 \ \forall \ m = 1,\ldots,N$ yielding the MNL specification.

$$I = I(y,\mathbf{p},\mathbf{q}) = \ln\left(\sum_{m=1}^{N}\left[\sum_{k \ni n(k)=m} e^{V_k(y-p_k,\mathbf{q}_k)/\theta_m}\right]^{\theta_m}\right), \qquad (5)$$

where $\mathbf{p} \equiv (p_1,\ldots,p_J)'$ and $\mathbf{q} \equiv (\mathbf{q}_1',\ldots,\mathbf{q}_J')'$. The inclusive value has been interpreted as a measure of the expected maximum utility from the site characteristics. Indeed, if the utility function in (2) is specified as linear in income, the compensating variation *per choice occasion* associated with a change in prices or environmental quality can be expressed analytically as[7]

$$C = \frac{1}{\beta_y}\left[I(y,\mathbf{p}^0,\mathbf{q}^0) - I(y,\mathbf{p}^1,\mathbf{q}^1)\right], \qquad (6)$$

where the superscripts on the price and quality attributes are used to distinguish the new (superscript 1) and original (superscript 0) levels and β_y is the marginal utility of income.[8] If the total number of trips taken by an individual (T) is unaffected by the these changes to the site prices and quality attributes, then the total compensating variation is simply $C \cdot T$. However, since T is unlikely to remain fixed, the second component is added to the linked model to capture possible changes in the participation decision. It is in the specification of the participation equation that the two components of the model are explicitly linked.

A generic form for the participation equation is given by

$$T = h(\mathbf{L},\mathbf{c},Y) + \mu, \qquad (7)$$

where **L** is a vector of variables that link the participation equation to the site selection model, **c** denotes a vector of other variables thought to explain total number of trips, Y denotes annual

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[7] See, for example, Small and Rosen (1981), Hanemann (1982,1998).

[8] If the utility function is nonlinear in income, there is no closed-form solution for the compensating or equivalent variation and numerical methods must be used (see McFadden (1996) and Herriges and Kling (1997)).

income and μ is a random error term. Three basic versions of the participation model in equation (7) have emerged in the literature, differing both in terms of the variables used to link the components of recreation demand and the methods used to extract welfare estimates.[9]

In the first variant, BHK suggest using the inclusive value (5) computed from the site selection model as an explanatory variable in the participation equation, noting that the inclusive value represents "the value of different alternatives weighted by their probabilities of being chosen." Thus the participation demand equation becomes

$$T = h_1(I, \mathbf{c}, Y) + \mu, \qquad (8)$$

where "I" is the inclusive value defined in (5). To compute overall welfare measures, BHK suggest using equation (6) to estimate the per choice occasion welfare effect of a policy change and to multiply this by the number of trips predicted by (8), computed at the new level of prices and/or qualities. Thus, the estimated total welfare change becomes:

$$W_1 = \frac{1}{\hat{\beta}_y}\left[\hat{I}\left(y, \mathbf{p}^0, \mathbf{q}^0\right) - \hat{I}\left(y, \mathbf{p}^1, \mathbf{q}^1\right)\right]\hat{h}_1\left[\hat{I}\left(y, \mathbf{p}^1, \mathbf{q}^1\right), \mathbf{c}, Y\right], \qquad (9)$$

where the carats are used to denote fitted parameters or models. Although this approach has intuitive appeal, the authors acknowledge that it is not fully utility theoretic. A variation on W_1 calculates total welfare (before and after a policy change) as the product of the predicted number

[9] Applications of the linked model have also differed in terms of the econometric techniques and functional forms used to estimate parameters for the participation equation, including tobit or Heckman models to account for the censoring of the data and various count data models that reflect the count nature of trip data.

of trips (h_1) and the monetized welfare per trip $\left(I/\beta_y\right)$.[10] The corresponding welfare measure naturally becomes:

$$W_1^* = \frac{\hat{I}^0\hat{h}_1^0}{\hat{\beta}_y} - \frac{\hat{I}^1\hat{h}_1^1}{\hat{\beta}_y}, \qquad (9')$$

Parsons and Kealy (1995) and Feather, Hellerstein, and Tomasi (1995) offer similar alternative representations of the linked model. Like the BHK variant, their models begin with estimation of a site selection model, followed by a participation equation. However, they do not use the inclusive value to link the models. Instead, they use the estimated probabilities associated with the alternatives from the site selection model to compute the "expected price" of a trip and the "expected quality" of a trip (PK refer to the latter as the expected utility of the trip). The expected price for each individual is computed as the sum of that individual's travel costs to the various sites weighted by the estimated probabilities of visiting each site. A similar weighting scheme is used for each site quality attribute. These variables are then used in the estimation of the participation model as

$$T = h_2(\overline{p}, \overline{\mathbf{q}}, Y) + \mu, \qquad (10)$$

where

$$\overline{p} = \sum_{j=1}^{J} \hat{\pi}_j p_j \ , \qquad (11)$$

$$\overline{\mathbf{q}} = (\overline{q}_1, \ldots, \overline{q}_K)' \qquad (12)$$

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[10] See, for example, Creel and Loomis (1992).

$$\bar{q}_k = \sum_{j=1}^{J} \hat{\pi}_j q_{jk} \ , \qquad (13)$$

and the $\hat{\pi}_j$'s are the predicted probabilities from equation (4).

In evaluating changing site price and/or quality attributes, FHT use a welfare measure analogous to equation (9), multiplying the per choice occasion compensating variation in (6) by the expected number of trips under the new attributes as predicted by the participation model in (10). PK, on the other hand, interpret the participation equation in (10) as the relevant demand equation and integrate under it with respect to price to yield consumer surplus measures of quality and/or price changes. Thus, the welfare change associated with the improvement in a single site attribute would be computed as

$$W_2 = \int_{\bar{p}^0}^{\bar{p}^1} \hat{h}_2(p, \bar{q}^0, Y)dp + \int_{\bar{q}^0}^{\bar{q}^1} \hat{h}_2(\bar{p}^1, q, Y)dq, \qquad (14)$$

where the superscripts indicate the level at which the expected prices and qualities are evaluated.

The final variant on the linked model was developed by Hausman, Leonard and McFadden (1995) and represents a blending of the first two approaches. Like BHK, HLM use a variant of the inclusive value to link the site selection and participation models, but they construct welfare measures using a consumer surplus argument similar to that employed by PK. The other major difference between the HLM approach and other variants on the linked model is that the authors claim their model is utility theoretic, consistent with a two-stage budgeting process. Authors of the other variants generally acknowledge that they are not "…derived from a single overall utility maximization problem," (Parsons and Kealy, 1995, p. 360) but instead represent a reasonable approximation to such a problem.

The site selection stage in HLM is identical to those in other linked models. The differences emerge at the participation stage, with[11]

$$T = h_3(\tilde{p}, Z, Y) + \mu, \qquad (15)$$

where *Z* is a vector of individual characteristic assumed to affect participation and

$$\tilde{p} \equiv \frac{-I(y, \mathbf{p}, \mathbf{q})}{\beta_y} \qquad (16)$$

is the negative of the per trip consumer surplus arising from recreation, which HLM interpret as a price index in a two-stage budgeting process. Equation (15) is then interpreted as the first stage in the budget allocation process, with the consumer deciding how much to spend on recreation. The site selection model represents the second stage in which the recreation budget is allocated among sites.

The ability to interpret the linked model of HLM as utility-consistent would provide a strong basis for choosing it from among the variants in the literature. Unfortunately, as recently noted by Smith (1997), the authors' proof of consistency relies upon an assumption that does not hold in general.[12] Specifically, HLM assume that:

$$T = \frac{y_F}{\tilde{p}} \qquad (17)$$

where

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[11] HLM model the number of trips as a count random variable.

[12] Shonkwiler and Shaw (1997) also demonstrate that a two-stage budgeting model, using total trips as the aggregator function for the participation stage and an MNL model for the site selection stage, cannot be derived from utility theoretic framework. They suggest an alternative to the linked model, using total distance traveled as the aggregator function for the participation stage, and demonstrate that their model can be derived from a utility theoretic framework.

$$y_F \equiv \sum_{j=1}^{J} p_j x_j \tag{18}$$

denotes the total level of expenditures allocated to recreation in the first stage, with x_j denoting the number of trips taken to site *j*. To see that equation (17) will not hold in general, consider the case in which the site selection model is MNL and the nonstochastic portion of the indirect utility function in equation (2) is given by the simplest of specifications; i.e.,

$$V_j = -\beta_y p_j, \quad j = 1, \ldots, J. \tag{19}$$

Under these circumstances, the price index in equation (16) becomes:

$$\tilde{p} = \frac{-1}{\beta_y} \ln\left(\sum_{j=1}^{J} e^{-\beta_y p_j} \right), \tag{20}$$

and the assumption in equation (17) corresponds to requiring that:

$$\sum_{j=1}^{J} x_j = \frac{\sum_{j=1}^{J} p_j x_j}{\frac{-1}{\beta_y} \ln\left(\sum_{j=1}^{J} e^{-\beta_y p_j} \right)}. \tag{21}$$

Clearly, this need not hold in general. Even for this simple specification, equation (21) will typically hold only if either (a) the prices for all of the sites are the same (in which case all of the sites are equivalent from the individual's perspective) or (b) $p_j < \infty$ for one site *j* and $p_k \to \infty \; \forall k \neq j$ (in which case only site *j* is visited). If the indirect utility V_j is allowed to be a more general function, including income and site quality attributes, even these conditions will not insure the desired equality in equation (17).

Thus, analysts employing linked models of recreation demand are left with the task of choosing from among three variants linking the site selection and participation stage, none of which derive from a unified utility theoretic framework, but each of which has at least some intuitive appeal as an approximation to the consumer's underlying problem. In our empirical section below, we employ the HLM participation model. The linking variable, $\tilde{p}$, has the attractive interpretation as the monetized utility per trip and, when the marginal utility of income is constant across individuals, the HLM model is equivalent (except for a scaling factor) to the more traditional BHK variant.

A second decision in applying the linked model of recreation demand is the choice of welfare measures. HLM, for example, treat their participation model as providing a demand equation for trips and estimate welfare changes using standard consumer surplus measures. Thus, the welfare change associated with a quality site improvement would be computed as

$$W_3 = \int_{\tilde{p}^1}^{\tilde{p}^0} \hat{h}_3(p, Z, Y)dp, \qquad (22)$$

This approach, however, is predicated on the consistency of their model with utility theory. Without this consistency, the interpretation of the participation model as a demand equation becomes questionable and it is no longer clear that areas under the participation curve correspond to consumer surplus. In the empirical section below, we compute welfare measures for the HLM model using both the welfare measure advocated by Creel and Loomis (1992), W_1^* of equation (9'). We also present the per choice occasion estimates from the site selection model alone.

Finally, despite the difficulties associated with the various linked models, they remain the dominant approach to integrating the site selection and participation decisions associated with recreation demand. This is due, in large part, to the ability of these models to handle a large number of recreation sites without having to resort to site aggregation. Furthermore, with recent improvements in computing power, analysts are now able to capture potentially complex substitution possibilities among sites in the site selection stage of the model using multinomial probit (see Chen, Lupi, and Hoehn, 1998), multi-level nested logit and random coefficient specifications (see Train, 1998).

6.2.2 The Kuhn-Tucker Model

The Kuhn-Tucker model, in contrast to linked models, relies upon a single structural framework to simultaneously model the site selection and participation decisions and to control for possible corner solutions. Initially developed by Wales and Woodland (1983) and Hanemann (1978) and refined by Bockstael, Hanemann, and Strand (1986), the Kuhn-Tucker model begins by assuming that individual preferences are randomly distributed in the population. By specifying a parametric form for the consumer's direct utility function, standard Kuhn-Tucker conditions can be used to identify the participation and site selection probabilities needed to estimate preferences and construct welfare measures.[13] Despite its appeal as a structural model, the Kuhn-Tucker model has received little attention in the applied literature, with only one application to the modeling of recreation demand (Phaneuf, Kling, and Herriges (1997), hereafter PKH). However, with recent advances in computing power, the burden of estimating this highly non-linear model have eased and additional applications may be forthcoming.

Formally, the Kuhn-Tucker model begins with the assumption that consumer preferences over the *J* alternative sites can be represented by a random utility function, which they maximize subject to a budget constraint and a set of non-negativity constraints. In particular, the consumer's problem is to

$$\underset{\mathbf{x},z}{Max}\ U(\mathbf{x},z,\mathbf{q},\gamma,\varepsilon) \qquad (23)$$

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[13] The Kuhn-Tucker approach can also begin with the specification of the indirect utility function, as outlined by Lee and Pitt (1986) and Bockstael, Hanemann, and Strand (1986).

s.t.

$$\mathbf{p}'\mathbf{x} + z = Y, \text{ and} \quad (24)$$

$$z \geq 0, x_j \geq 0, \quad j = 1,\ldots,J, \quad (25)$$

where $U(\cdot)$ is assumed to be a quasi-concave, increasing, and continuously differentiable function of $(\mathbf{x}, z)$, $\mathbf{x} \equiv (x_1,\ldots,x_J)'$ is the vector of sites specific trips, z is the numeraire good which is assumed to be necessary, $\mathbf{p} \equiv (p_1,\ldots,p_J)'$ is a vector of site prices, $\mathbf{q} \equiv (\mathbf{q}_1',\ldots,\mathbf{q}_J')'$ is a vector of site attributes, γ is a vector of parameters, and $\varepsilon \equiv (\varepsilon_1,\ldots,\varepsilon_J)'$ is a vector of random disturbances capturing the variation of preferences in the population.

The first-order necessary and sufficient Kuhn-Tucker conditions for the utility maximization problem can be written[14]

$$\begin{aligned} U_j(\mathbf{x}, Y - \mathbf{p}'\mathbf{x}; \mathbf{q}, \gamma, \varepsilon) &\leq U_z(\mathbf{x}, Y - \mathbf{p}'\mathbf{x}; \mathbf{q}, \gamma, \varepsilon)\, p_j, \\ x_j &\geq 0, \\ x_j\left[U_j - U_z p_j\right] &= 0, \end{aligned} \quad (26)$$

for $j = 1,\ldots,J$, where $U_j \equiv \partial U / \partial x_j$ and $U_z \equiv \partial U / \partial z$. By invoking some simplifying assumptions (i.e., $\partial U_j / \partial \varepsilon_k = 0 \ \forall k \neq j \quad \partial U_j / \partial \varepsilon_j > 0 \ \forall j = 1,\ldots,J$, and $U_{z\varepsilon} = 0$), these first-order conditions can be rewritten as

$$\begin{aligned} \varepsilon_j &\leq g_j(\mathbf{x}, Y, \mathbf{p}; \mathbf{q}, \gamma), \\ x_j &\geq 0, \\ x_j g_j(\mathbf{x}, Y, \mathbf{p}; \mathbf{q}, \gamma) &= 0 \end{aligned} \quad (27)$$

[14] Additional details of the model specification can be found in Phaneuf, Kling, and Herriges (1997).

for $j = 1,\ldots, J$. Equation (27), along with the specification of the joint density function $f_\varepsilon(\cdot)$ for ε, provides the necessary information to construct the likelihood function. For example, an individual who chooses to visit only the first k sites (i.e., $x_j > 0 \;\; j = 1,\ldots, k$ and $x_j = 0$ for $j = k+1,\ldots, J$) contributes the following term to the likelihood function:

$$\int_{-\infty}^{g_{k=1}} \cdots \int_{-\infty}^{g_M} f_\varepsilon(g_1,\ldots,g_k,\varepsilon_{k+1},\ldots,\varepsilon_M)\, abs\left|J_k\right|\, d\varepsilon_{k+1}\cdots d\varepsilon_M \qquad (28)$$

where J_k denotes the Jacobian for the transformation from ε to $(x_1,\ldots,x_k,\varepsilon_{k+1},\ldots,\varepsilon_J)'$. There are 2^J possible combinations of sites visited and the similar contribution to the likelihood function can be constructed for each.

Conceptually, this Kuhn-Tucker model of recreation demand is appealing, providing a unified and utility theoretic framework for modeling both the participation and site selection decisions. Furthermore, unlike the linked model, it is unified econometrically, with a single error structure driving both participation and site selection. These features of the model, however, come at a cost. The associated likelihood function is highly nonlinear, increasing in complexity as the number of available sites increases, with the number of possible Jacobian terms doubling with each additional site. This has led those applying the Kuhn-Tucker model to date to rely upon relatively simply specifications for the direct utility function and error structures that yield closed form choice probability expressions.[15]

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[15] To be fair to the Kuhn-Tucker model, these same type of assumptions have dominated the site selection stage of the linked models appearing in the literature. Only recently, have analysts departed significantly from the traditional MNL or NL error specifications and linear functional forms for the nonstochastic portion of site utility (i.e., V_j in equation 2).

In the empirical section below, we follow PKH by using the direct utility function originally suggested by Bockstael, Hanemann, and Strand (1986), with

$$U(\mathbf{x}, z, \mathbf{q}, \gamma, \varepsilon) = \sum_{j=1}^{J} \psi_j(q_j, \varepsilon_j)\ln(x_j + \theta) + \ln(z)\,, \qquad (29)$$

where

$$\psi_j(q_j, \varepsilon_j) = \exp\left(\sum_{s}^{S} \delta_s q_{js} + \varepsilon_j\right) \quad j = 1, \ldots, J\,, \qquad (30)$$

$\gamma = (\delta, \theta)$ and q_{js} denotes the s[th] quality characteristics associated with site j. In this model, weak complementarity holds if $\theta = 1$. The functional form for the g_j in equation (27) becomes

$$g_j(\mathbf{x}, y, \mathbf{p}; \mathbf{q}, \gamma) = \ln\left[\frac{p_j(x_j + \theta)}{Y - \sum_{k=1}^{J} p_k x_k}\right] - \sum_{s=1}^{S} \delta_s \quad j = 1, \ldots, M. \qquad (31)$$

In addition, we assume that the ε_j's are independent and identically distributed negative extreme value variates with parameters $\eta = 0$ and λ. Given these assumptions, the likelihood terms in equation (28) become:[16]

$$\exp\left(-\sum_{j=1}^{k} \frac{g_j}{\lambda}\right) abs\left|J_k\right| \exp\left[-\sum_{j=1}^{J} \exp\left(\frac{-g_j}{\lambda}\right)\right]. \qquad (32)$$

We now turn to welfare measurement using the Kuhn-Tucker model. If $V(\mathbf{p}, Y; \mathbf{q}, \gamma, \varepsilon)$ denotes the solution to the utility maximization defined in equations (23) through (25) above, then the

[16] General expressions for the likelihood function's terms and the associated Jacobians can be found in PKH.

compensating variation (C) associated with a change in the price and attribute vectors from ($\mathbf{p}^0$,$\mathbf{q}^0$) to ($\mathbf{p}^1$,$\mathbf{q}^1$) can be implicitly defined by

$$V(\mathbf{p}^0, Y; \mathbf{q}^0, \gamma, \varepsilon) = V(\mathbf{p}^1, Y + C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, Y; \gamma, \varepsilon); \mathbf{q}^1, \gamma, \varepsilon) . \qquad (33)$$

Note that $C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, Y; \gamma, \varepsilon)$ is a random variable and that the nonlinearity of the functions will generally make numerical techniques necessary for its solution. PHK describe in detail a numerical algorithm for computing the expected compensating variation associated with a price or quality change. We briefly summarize the procedure here. Given an estimator of γ, say $\hat{\gamma} \sim g_{\hat{\gamma}}$, a large number of parameter vectors ($\gamma^{(i)}, i = 1, \ldots, N_\gamma$) are drawn from $g_{\hat{\gamma}}$. For each $\gamma^{(i)}$, Monte Carlo integration is used to construct $\hat{C}^{(i)} \equiv E_\varepsilon\left[C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, Y; \gamma^{(i)}, \varepsilon)\right]$ by drawing a series of disturbance vectors ε from f_ε and using numerical bisection to solve for C in equation (33) for each draw of ε. Averaging over the C's generated in this manner yields a consistent estimate of $\hat{C}^{(i)}$ given $\gamma^{(i)}$. The empirical distribution of the $\hat{C}^{(i)}$'s can in turn be used to construct confidence intervals on the average compensating variation. The complexity of the welfare calculations in the Kuhn-Tucker model represent another drawback to their use, but one which should diminish as computing power improves.

6.2.3 The Repeated Nested Logit Model

A third framework used in the literature to combine the recreational site selection and participation decisions is the repeated nested logit (or RNL) model developed by Morey, Rowe, and Watson (1993) (hereafter MRW). Here, we provide a brief overview of this approach, but, due to space constraints, do not estimate the RNL model in our empirical section. A detailed discussion of this model can be found in MRW and Morey, et al. (1995).

At the heart of the RNL model are two assumptions. First, the recreation season is assumed to consist of a fixed number of choice occasions (*S*), during which each recreationist is assumed to make at most one trip. For example, in MRW, the authors assume that *S*=50, dividing the year into roughly one week intervals. Second, the choice occasion decisions are assumed to be independent not only across individuals, but also across choice occasions for the same individual. Thus, where and whether an individual chooses to participate during a given occasion is assumed to be independent of previous recreation choices. These two assumptions enable MRW to jointly model the participation and site selection decisions as an extension of the basic site selection model.

Formally, during a given choice occasion, the individual faces *J+1* alternatives, the possibility of visiting one of *J* sites or choosing not to recreate at all, with the utility of alternative *j* on choice occasion *s* given by:

$$U_{js} = V_{js} + \varepsilon_{js}, \; j = 0, 1, \ldots, J. \qquad (34)$$

Choosing alternative $j = 0$ corresponds to not traveling during that choice occasion. The error vectors $\varepsilon_s \equiv (\varepsilon_{0s}, \ldots, \varepsilon_{Js})'$ are assumed to be distributed independently across both choice occasions and individuals. For a given choice occasion and individual, MRW assume that the error terms (i.e., the ε_s's) are drawn from a generalized extreme value distribution yielding nested logit choice probabilities. In the first level of the nest, the individual chooses whether or not to recreate, with subsequent nesting levels used to distinguish which sites are visited if they choose to recreate.

The primary advantage of the RNL framework is that, given the two assumptions outlined above, the model yields a utility theoretic approach to combining the site selection and participation decisions that is relatively easy to estimate and construct welfare measures for. Unfortunately, as Morey, *et al.* (1995) note, the two assumptions required to make the model utility theoretic are nontrivial. The number of choice occasions is assumed to be exogenously determined and the same for all recreationists. Furthermore, it must be chosen by the analyst. To our knowledge, there is no research available regarding the impact that choice of *S* has on the welfare measures computed using the RNL model. The second assumption (i.e., that participation and site selection decisions are independent across choice occasions and individuals) is also questionable, precluding habit formation or learning from past experiences. It should be noted, however, that a similar assumption underlies the site selection stage of most linked models. While some studies estimate their site selection model using data on an individual's most recent trip (e.g., Kling and Thompson (1996)), most employ a complete enumeration of individual's trips during a season (e.g., Creel and Loomis (1992) and BHK). Each trip is then treated as an independent observation on site selection, assuming away any correlation among trips made by the same individual. While recent advances in computing power may soon allow for a panel data approach to the analyzing site selection data, the current state of the art for both the RNL and site selection is to treat trips as independent across choice occasions.

6.2.4 Other Noteworthy Approaches

There are a handful of alternative models that can also handle corner solutions. Although space is too limited here to provide a thorough presentation and analysis, we wish to mention the models for completeness and because in some cases, these models may provide attractive alternatives to the linked, Kuhn-Tucker, or repeated nested logit models. The first category of alternative models falls under the rubric of systems of demand equations. One of the first such models in recreation is a study of the value of introducing an additional set of lakes in southern Missouri by Burt and Brewer (1971). In addition to estimating a system of demands, they also tested for and imposed symmetry of the cross-price effects to assure the path independence of their consumer surplus measures. Cichetti, Fisher, and Smith (1976) also provide an early application of systems of demands. A recent application of demand systems by Ozuna and Gomez (1994) estimates count models using seemingly unrelated regression techniques. The varying parameter models of Vaughan and Russell (1982), Smith, Desvousges, and McGivney (1983) and Smith and Desvousges (1985)), among others provide additional examples of systems of demand equations with a specific focus on environmental quality. To deal with corner solutions, these models would need to be modified to account for the effect of corners on the structure of demand equations. Most notably, when an individual does not visit (consume) one of the sites, the prices and qualities of that site drop out of the demand equation (see Phaneuf, Kling, and Herriges (1997)).

In an approach closely aligned to systems of equations, Morey (1981, 1984, 1985) specifies and estimates a system of share equations. Although commonly estimated in the general demand literature, systems of share equations have seen little application in recreation demand. To adequately accommodate corners, the probability of shares equal to zero must be nonzero.

A final approach worth mentioning is the innovative model developed by Provencher and Bishop (1997) which explicitly accounts for the intraseasonal dynamic nature of the problem. Such an approach holds promise to better understand the continuous decision of how many trips recreationists take in a season.

6.3 THE DATA

The data set used below to estimate and compare the linked and Kuhn-Tucker models of multiple site recreation demand concerns angling behavior in the Wisconsin Great Lakes region. The usage data come from two mail surveys of angling behavior conducted in 1990 by Richard Bishop and Audrey Lyke at the University of Wisconsin-Madison.[17] The surveys provide detailed information on the 1989 angling behavior of Wisconsin fishing license holders, including the

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[17] Details of the sampling procedures and survey design are provided in Lyke (1993). We are grateful to Richard Bishop and Audrey Lyke for providing us with data. Any errors in using the analysis of their data are, of course, our own.

number and destination of fishing trips to Wisconsin Great Lakes region, the distances to each destination, the type of angling preferred, and the socio-demographic characteristics of the survey respondents. A total of 487 completed surveys were available for analysis, including 240 individuals who had visited one or more of the 22 destinations identified for the Wisconsin Great Lakes region and 247 who fished only inland waterways (i.e., non-users from the perspective of the Great Lakes region).[18] We have aggregated the destinations of Great Lakes anglers into four sites: Lake Superior, South Lake Michigan, North Lake Michigan, and Green Bay. Kaoru, Smith, and Liu (1995) and Parsons and Needelman (1992) discuss the implications of site aggregation decisions in recreation demand, specifically for the case of RUM models. At issue is the fact that the analyst must define what constitutes a choice alternative and which alternatives the recreationist considers. Misspecification of the choice set can lead to biased parameter estimates, and benefit estimates tend to be sensitive to aggregation decisions. Although Parsons and Kealy (1992) have demonstrated a method for avoiding aggregation in RUM models by randomly drawing each individual's choice set from a large universe of sites, most authors have relied on characteristics of the available data and common sense to make aggregation decisions.

The aggregation strategy for this study divides the Wisconsin portion of the Great Lakes into distinct geographical zones consistent with the Wisconsin Department of Natural Resources classification of the lake region. The degree of aggregation in this study is less an issue than in those cited above, since the variation in the physical characteristics of the destinations in each site is small compared to the large geographical differences in the four sites. Table 9.1 summarizes

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[18] These sample figures do not include the 22 recreationists excluded from our analysis who reported more than fifty recreation trips during the 1989.

both the average number of trips to and percentage of the sample visiting each of the aggregate sites.

The price of a trip to each of the four fishing sites consists of both the direct cost of getting to the site and the opportunity cost of the travel time. Round trip direct travel costs were computed for each destination and each individual by multiplying the number of round trip miles for a given individual-destination combination by the cost per mile for the vehicle class driven, as provided by the American Automobile Association. The cost of the travel time was constructed using one-third of the individual's wage rate as a measure of the hourly opportunity cost of recreation time and assuming an average travel speed of forty-five miles per hour to compute travel time.[19] The price of visiting a destination (i.e., p_j) is then the sum of these two components.[20] As indicated in Table 9.1, the cost of visiting the Great Lakes sites averaged between $86 per trip for South Lake Michigan to $178 per trip for the more remote Lake Superior region.

Two household characteristics are included in the estimated linked and Kuhn-Tucker models, annual income and a dummy variable indicating boat ownership. For the sample as a whole, income averaged just under $44,000 per year, with almost 22 percent owning their own boat.

Two types of quality attributes (i.e., q_{jk}'s) are used to characterize the four recreation sites: fishing catch rates and toxin levels. In constructing the catch rate variables, we focus our attention on the catch rates for the four aggressively managed salmonoid species: lake trout, rainbow trout, coho salmon, and chinook salmon. Creel surveys by the Wisconsin Department of Natural

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[19] Data on trip lengths were not available, so that it was necessary to assume that on site time was constant for all trips.

[20] Prices are calculated for each individual for each destination. The price of the site is the price of the most frequently visited destination if the site was visited, or the average of the destinations if it was not. The site attribute variables described below are similarly computed. See Phaneuf (1997) for further details on variable descriptions.

Resources provide catch rates for each of these species that are broken down by angling method, including private boat, charter fishing, and pier/shore angling. Catch rates for the four species were formed for each individual-destination pair. Catch rates for each of the four aggregate zones were then formed as the catch rates of the most frequently visited destination within that zone if it was visited, or the average of the catch rates within that zone if it was not. Data from the Wisconsin angling survey were used to match the mode-specific catch rates to each individual angler based upon their most frequent mode of fishing.

The second site characteristic used in our empirical analysis is toxin levels. De Vault *et al.*(1989) provide average toxin levels in lake trout (ng/kg-fish) for locations throughout the Great Lakes region. These were matched on the basis of proximity to our four aggregate sites to form a basic toxin measure for each site, T_j j=1, …,4.[21] However, since toxin levels are likely to influence visitation decisions only if the consumer perceives a safety issue, we use information from the Wisconsin angling survey to form an "effective toxin level" variable $E_j \equiv T_j D$ for j=1,…,4, where D=1 indicates that the respondent was concerned about the toxin levels in fish and D=0 otherwise. As one might expect, the effective toxin levels, summarized in Table 9.1, are highest at the South Lake Michigan site, surrounded by densely populated and industrial communities of Chicago, Milwaukee and Gary, Indiana.

[21] While there are a variety of toxins reported in the De Vault *et al.*(1989) study, we use the levels of toxins 2-,3-,7-, and 8-TCDD, which are generally responsible for the fish consumption advisories issued by states in the region.

6.4 RESULTS

In this section we provide details of the empirical specification and resulting parameter estimates, followed by a series of welfare measures based upon the competing linked and Kuhn-Tucker models.

6.4.1 MODEL SPECIFICATION AND PARAMETER ESTIMATES

The Linked Model. As in any empirical exercise, in addition to selecting the variables to include in the estimation, it is also necessary to select functional forms and error structures for the estimating equations. In the case of the linked model, there are two components or stages and thus two estimating equations that must be specified. Ideally, the error terms and functional forms of these equations would be specified so that they were wholly consistent with one another and derivable from a unified structural model of consumer preferences. However, as noted in Section 9.2.1, the linked model is not utility theoretic and, hence, requires the use of separate reduced form equations for each stage.

The site selection model in equation (1) requires the specification of both the nonstochastic (V_j) and stochastic (ε_j) elements of the model. We have chosen to estimate two distinct functional forms for V_j: a linear form and a Generalized Leontief (GL). It was our intention to choose a form that has been commonly estimated (the linear specification) as well as one that can be viewed as a second order approximation (the Generalized Leontief). The stochastic elements are assumed to be drawn from a generalized extreme value distribution, yielding the nested logit site selection probabilities in equation (4), with an underlying nesting structure that groups the North and South Lake Michigan sites (See Figure 1). The two Lake Michigan sites are the most similar in terms of both their physical characteristics and fishing stocks.

Table 9.2 provides parameter estimates for three variants of the site selection model. The first variant (S1) employs an indirect utility function that is linear in $(y-p)$, the effective toxins level E, and each of the four catch rate variables (R_i, i = lake trout, chinook salmon, coho salmon, and rainbow trout).[22]. The coefficients on $(y-p)$ and toxins are of the expected signs and statistically significant at the 1 percent level, but the signs on the four catch rate variables do not conform well to our expectations. Although coho and rainbow both exhibit significantly positive effects, both lake trout and chinook exhibit significantly negative effects. The dissimilarity coefficient, θ, is estimated to be 1.47 and is significantly greater than 1.00, suggesting that the nested structure provides a better fit of the data than a straight multinomial logit model. However, an inclusive value coefficient that is greater than 1.00 also suggests that the model is inconsistent with the random utility maximization hypothesis.[23]

We view the large inclusive value coefficient and the unintuitive signs on the catch rate variables to indicate that this first variant of the site selection model may be mis-specified. Thus, we investigate an alternative formulation. In particular, rather than enter each catch rate variable alone, we use the following catch rate index:

$$R_I \equiv \sum_i R_i \overline{F}_i \qquad (35)$$

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[22] In the estimation, $(y-p)$ is measured in terms of units of \$10,000, with the per-choice-occasion income (*y*) defined as monthly income. The choice of units used in measuring income is important only when there are non-linear income effects in the site selection model, as is the case in the GL site selection model (S3).

[23] The requirement that the inclusive value lie in the unit interval for consistency with utility maximization can be relaxed if the analyst is concerned only with consistency locally (see Börsch-Supan (1990) and Herriges and Kling (1995)).

where $\overline{F_i}$ denotes the percentage of angler indicating that they were fishing for the i^{th} fish species (i = lake trout, etc.). Summary statistics for R_I are provided by site in Table 9.1.

Using this catch rate index (R_I) in a linear functional form yields our second variant on the site selection model (S2), with parameter estimates reported in column 2 of Table 9.2. In this model, all variables exhibit the anticipated signs and the standard error estimates support statistical significance of the variables. Furthermore, the dissimilarity coefficient is no longer significantly different from 1.00, yielding consistency with the RUM hypothesis.

Our third variant on the site selection model (S3) uses the nonlinear Generalized Leontief form for the indirect utility function. For this specification, we used the catch rate index just discussed rather than the four separate catch rate variables. This choice was made partly for expedience (the Generalized Leontief places large demands on the data) and partly based on the results from the two linear specifications. The resulting coefficient estimates are reported in the third column of Table 9.2. While the parameters in this nonlinear model are more difficult to interpret than their linear counterparts, they are all statistically significant at a 95 percent confidence level. Furthermore, the parameters can be used to determine for each individual and site combination the marginal utilities of income, toxins, and catch rate. As one would hope, the marginal utility of income is positive and declining with income.[24] Similarly, the marginal utility of fish catch rates is positive and diminishing. Finally, toxins have the expected negative impact on utility, with a marginal utility of -.17 on average over the sample. Turning to the dissimilarity coefficient, we find that θ is estimated to lie within the unit interval and is significantly different from 1.00 at the 99 percent confidence level. This suggests both consistency of the model with utility maximization and the superiority of the nested structure to a straight multinomial logit model. Finally, we note

[24] On average, the marginal utility of income is 0.02, ranging from 0.008 to 0.05 over the sample.

that the nonlinear Generalized Leontief specification yields a significant reduction in the log likelihood function, with a likelihood ratio test of the restriction of GL model to the linear model rejected at 1 percent significance level.

The site selection model provides the first stage in the linked model's representation of recreation demand. The second component of the linked model requires the specification of the participation equation. Based on the discussion of the alternative approaches in section 9.2.1, we have adopted the HLM strategy for linking the two components. Thus, we use the index $\tilde{p}$ from equation (16) (i.e., the negative of the per trip consumer surplus) as the linking variable. Since there are three different site selection models estimated, we estimate a separate participation equation for each of these indices. The computation of $\tilde{p}$ for the two linear site selection models is straightforward; it is simply the inclusive value defined in equation (5) divided by the estimated marginal utility of income (the coefficient on $(y-p)$). However, in the Generalized Leontief model, there is no simple analog. By construction, the marginal utility of income is not constant so a single parameter does not represent its value. However, it is still straightforward to compute the inclusive value following equation (5). In order to monetize this value, we have computed the estimated marginal utility of income for each individual at their current consumption levels and use this in place of β_y in equation (16). Although each individual's marginal utility of income will change with deviations from that point, this value provides a first order approximation and, for want of a better alternative, seems to be a reasonable way to implement HLM version of the linked model when the site selection model is nonlinear in income.

Two functional forms are used in estimating the participation equation: linear and Generalized Leontief. Since there are three site selection models that can be used to form $\tilde{p}$, a total of six participation models result. In addition to the index, $\tilde{p}$, each equation contains a constant term, annual income (y) and a dummy variable taking on the value of "1" if the respondent owns a boat and fishes by boat, and "0" otherwise (B). Finally, since our data is censored (about half of the sample take no angling trips to the Wisconsin Great Lakes fisheries), we use a Tobit estimator.

The first three columns in Table 9.3 present the estimated coefficients for linear participation equations (labeled models L1 through L3). In all three of these models, the ownership of a boat has the expected positive impact on participation, increasing the number of trips per year by roughly 12 under all three specifications. However, the coefficients on $\tilde{p}$ and y are both less consistent with our expectations and among the various specifications. For example, HLM interpret $\tilde{p}$ as a price index and anticipate a corresponding negative coefficient. Given that the model is not consistent with utility theory, we avoid this interpretation of $\tilde{p}$. Nonetheless, one would still expect that, as the consumer surplus per trip decreases (and $\tilde{p}$ increases), the total number of trips would decline. Unfortunately, in model (L1) the coefficient on the index $\tilde{p}$ is not of the anticipated sign. In the other two linear models, the price coefficient is of the correct sign, but is statistically significant at the 5% level in model (L2). The income term is also only significant in model L2 and suggests, in that case, that angling in this region is an inferior good.

Columns 4-6 of Table 9.3 contain the results from using a Generalized Leontief functional form for the participation stage (with the models labeled G1 through G3). The choice of the first stage site selection model (used in constructing $\tilde{p}$) has much greater influence on the parameter estimates of these specifications than in the linear case. Many of the parameters change sign and/or size moving among the three nonlinear specifications. Furthermore, the importance of using a nonlinear participation model appears to depend on the site selection model to which it is linked. It is only in the case of model G2 that the generalization to the nonlinear specification yields a significantly improved fit, based on a likelihood ratio test of linear models as restrictions on the corresponding GL model. Interestingly, the estimates of σ are quite stable across all six of the models.

The Kuhn-Tucker Model. To provide the most apt comparison possible with the linked models, we have estimated two versions of the Kuhn-Tucker model outlined in Section 9.2.2, equations (29) through (31). In the first version (K1), we use four separate catch rate variables, while in the second version (B) we use only the catch rate index.[25] Both versions also include a constant, the "effective" toxins variable *E* described in the previous section, and the dummy variable (*B*) indicating the ownership of a boat, as well as site prices and income.

Table 9.4 contains the coefficient estimates from the two specifications of the Kuhn-Tucker model. In general, the coefficients have the expected signs and, with the exception of the coefficient on lake trout catch rates, are statistically different from zero at a 5 percent critical level or better. Furthermore, unlike the linked model, the parameter estimates obtained using the Kuhn-Tucker framework are remarkably consistent across the two specifications of the catch rate variables. In both models, higher toxin levels significantly reduce the perceived quality of a site, whereas the ownership of a boat increases the utility obtained from site visitation. Higher catch rates also enhance site quality, with marginal improvements in the catch rates of Chinook salmon and rainbow trout having the largest impact. Even the negative and statistically insignificant impact of lack trout catch rates on perceived site quality is not unexpected since, among anglers, lake trout

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[25] We began this analysis assuming that we would only use the four separate catch rate variables as we had previously estimated the K-T model on this data using individual catch rates with good results (see Phaneuf, Kling, and Herriges (1997)). However, as noted above, the results were less than appealing when these same variables were used in the linked model. Thus, we felt an alternate specification was warranted to provide comparisons among the models and to put the linked model in the best possible light. Note also that the results reported in Phaneuf, Kling, and Herriges (1997) omit the "Boat" variable and use slightly more observations than the results reported here.

are typically considered to be a less desirable species. The coefficient on aggregate catch rate (*R*) is also positive, lying roughly at the average level of the individual catch rate coefficients, and is statistically different from zero using a 1 percent critical level.

The other coefficient of interest is θ. As noted in PKH, the Kuhn-Tucker model in equations (29) through (31) does not impose weak complementarity, an assumption used throughout the recreation demand literature. Weak complementarity implies that all value associated with a recreational site consists of use value alone, precluding non-use value. In our Kuhn-Tucker model, weak complementarity holds only if $\theta = 1$. The models presented in Table 9.4 suggest that weak complementarity is rejected in the current application, with θ being significantly different from 1 at a 5 percent critical level under both specifications and suggesting that there is non-use value associated with the Great Lakes region.[26]

6.4.2 WELFARE ESTIMATES

Because the linked and the Kuhn-Tucker models are distinct approaches with different underlying structures, functional forms, and error assumptions, the results of estimation are not directly comparable. Caution must also be exercised in concluding from these results that one approach is uniformly superior to the other, since the performance of the models depends not only on the framework chosen but also on assumptions made within the framework. Nonetheless both approaches provide the means to arrive at the same ends. Both models can be used to estimate the welfare changes associated with changing the price and quality attributes of sites within the Great

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[26] The rejection of weak complementarity in the current model is, of course, not a general test of the weak complementarity assumption, but conditional upon the specific functional form being employed here. One might extend the current model, for example, by allowing the θ_j's to vary by site and test for weak complementarity with respect to a subset of sites.

Lakes region. In this section, the modeling frameworks are used to evaluate the welfare implications of three policy scenarios:

- Scenario 1: Reduced Toxin Levels. Under this first policy scenario, we consider the welfare implications of a twenty percent reduction in the effective toxin levels at all four sites (i.e., $E_j,\ j = 1,\ 2,\ 3,\ 4$).
- Scenario 2: Loss of Lake Michigan Coho Salmon. Under this policy scenario, state and local efforts to artificially stock Coho salmon in Lake Michigan and Green Bay would be suspended. It is assumed that the corresponding Coho catch rates (i.e., $R_{coho\ salmon}$) would be driven to zero for all but the Lake Superior site. The aggregate catch rate variable (i.e., *R*) would be affected through changes to the individual catch rate components in equation (35).
- Scenario 3: Loss of the South Lake Michigan Site. Under this final policy scenario, use of the South Lake Michigan portion of the Great Lakes region would be suspended. This change is represented conceptually in the recreation demand models sending the price of visiting South Lake Michigan to infinity.

For each policy scenario, we compute the total welfare reduction associated with the policy for each of the six linked models and for the two variations on the Kuhn-Tucker model. The welfare measure used for the linked models is W_1^* defined in equation (9'), whereas the compensating variation of the policy shift, implicitly defined by equation (33), is used for the Kuhn-Tucker models. Finally, since some studies in the literature focus only on estimating welfare changes per choice occasion, abstracting from changes in the total number of trips, we provide per choice occasion welfare estimates for each policy scenario using the three site selection models in Table 9.2. The complete set of welfare measures are provided in Table 9.5.

Examination of the welfare estimates yields a number of conclusions. First, the linked model's welfare measures are quite sensitive to model specification (e.g., whether individual catch rates are used, as in models L1 and G1, or an aggregate catch rate is used, as in models L2 and G2). For example, since the toxin reduction under policy scenario 1 represents a improvement in environmental conditions, one would expect the welfare loss to be negative. This is the case for only half of the linked models, with the welfare loss estimated to range from \$146 to -\$314 per year. Second, the difficulties associated with the linked model's welfare measures emerge at both the site selection and participation stages. Thus, while the site selection models (S1 through S3) all yield negative *per choice occasion* welfare losses due to the toxin reduction, the point estimates differ by orders of magnitude across the three model specifications. Despite the consistency in sign on these per choice occasion welfare losses, the participation stage of the linked model often converts these to a positive welfare loss *per year*, due in large part to the fact that the coefficient on the index $\tilde{p}$ is of the wrong sign, predicting that the number of trips decreases with an increase in per choice occasion welfare.[27] In contrast, the Kuhn-Tucker model's welfare measures both have the expected negative signs and fall within a relatively narrow range (-\$60 to -\$74).

The welfare measures for policy scenarios two and three follow a similar pattern. The extinction of Coho salmon is estimated to yield a welfare loss per choice occasion of only \$8 when the linear aggregate catch rate site selection model is used (S2). This loss in increased five-fold if either individual catch rates are used (S1) or a nonlinear specification is employed (S3). While the corresponding annual welfare loss are more consistent in sign, they continue to range widely. In the case of loosing the South Lake Michigan site, the welfare loss ranges from -\$2404 to \$3148. In

[27] HLM experienced similar problems with their application of the linked model to Alaskan recreation, obtaining a positive coefficient on their price index variable in two of their four participation models.

contrast, the Kuhn-Tucker model's welfare predictions are relatively insensitive to the model specification.

6.5 FINAL COMMENTS

In this chapter, we have discussed the linked and Kuhn-Tucker frameworks for modeling recreation demand from both conceptual and empirical perspectives. Although the models are conceptually quite different, both approaches can be used to estimate the welfare effects of changes in site attributes, which can then be compared. The primary strength of the Kuhn-Tucker approach lies in the unified and utility theoretic framework it provides for modeling both the site selection and participation decisions and which can be used to derive utility theoretic welfare measures based on compensating or equivalent variation. In contrast, despite the intuitive appeal of its components, the linked model cannot be derived from a common underlying specification of preferences. Furthermore, it is not clear which of the competing welfare measures identified in the literature is preferred, since there is not a utility theoretic model from which they can be derived.

The strength of the linked model lies in the ease with which it can be estimated and used to compute welfare measures. The traditional nested logit model of site selection can be employed even when there are a large number of sites/alternatives available to recreationists. Furthermore, if the analyst is willing to assume a constant marginal utility of income, closed form expressions exist for the per choice occasion welfare effect of a policy change. In contrast, the complexity of the Kuhn-Tucker model has limited its use to date to problems involving relatively few alternatives, with both the stochastic and nonstochastic components of consumer preferences restricted to relatively simply functional forms. Furthermore, the welfare measures, while utility theoretic, require numerical methods to construct. It should be noted, however, that these advantages of the linked model have diminished over time for several reasons. First, efforts to relax the restrictive nature of the nested logit site selection models (e.g., Train, Chen, *et al.,* and Herriges and Kling), have increased the computational burden associated with both their estimation and welfare predictions, restricting in turn the number of choice alternatives they can be used to model. Second, recent increases in computing power have significantly diminished the burden of computing welfare measures for Kuhn-Tucker models and open the door to relaxing the functional forms used within this framework.

In the application of the Kuhn-Tucker and linked models to the specific case of Great Lakes angling, it appears that the Kuhn-Tucker model performs better. The welfare measures resulting from the various specifications of the linked model are sensitive to specification for both the seasonal and per choice occasion measures. Welfare effects also vary by magnitude and sign across the specifications, with no clear basis for choosing among the competing measures. In contrast, the Kuhn-Tucker model yields welfare measures that have the expected signs, are reasonable in magnitude, and which are stable across the two specifications for the model.

The fact that the Kuhn-Tucker model appears to outperforms the linked models in this specific case should not be interpreted to mean it is always the preferred model. As noted in section 9.2 the use of the Kuhn-Tucker model requires aggregation of possible recreation destinations into a small number of sites. In the case of the Great Lakes study, it was possible to aggregate in a geographically consistent manner such that the sites themselves exhibited distinct characteristics, while the destinations within the sites did not vary greatly. For other applications the aggregation strategy may not be so straightforward, and relevant information may be lost in the aggregation. In these types of applications, the linked model may be preferred based on its ability to handle a large number of available sites, with the information lost in using two reduced forms for estimation justified based on the information gained in site variability.

Analysts modeling multiple site recreation demand problems with data sets exhibiting a prevalence of corner solutions in the future will need to choose the modeling framework based on the number of sites being modeled, the aggregation options, and the availability of computer resources. If the number of sites is small or a natural aggregation strategy exists, the Kuhn-Tucker model is likely the best choice. If there are many alternatives, for which the sites within a geographical proximity are quite different from each other, the loss of utility consistency may be offset by the information gained in keeping the unique sites separate.

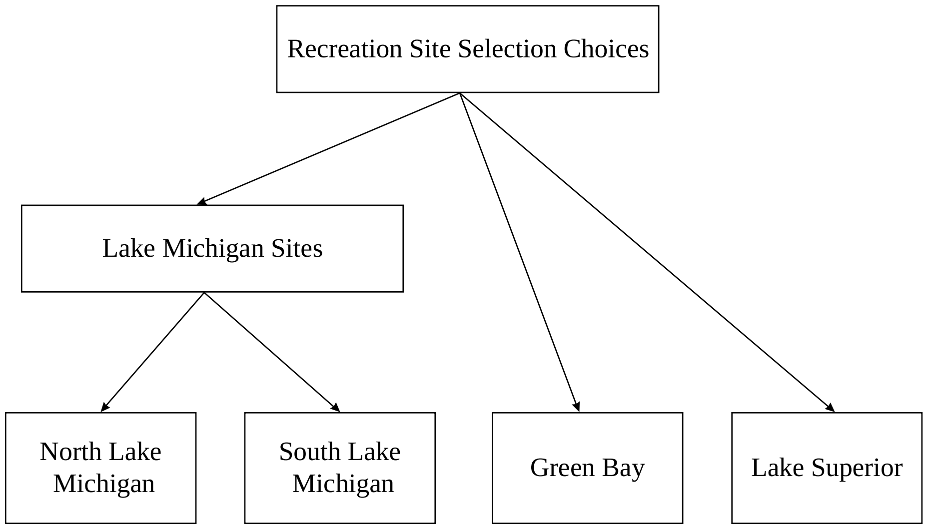

Figure 9.1: Nested Logit Model Structure

Table 9.1 Data Summary Average Site Characteristics

	Lake Superior	North Lake Michigan	South Lake Michigan	Green Bay
Fishing Trips	2.75 (13.33)	1.56 (6.32)	2.35 (8.92)	0.65 (3.07)
Percentage Visiting Site	13.1 (33.8)	20.5 (40.4)	23.2 (42.3)	9.9 (29.8)
Price	177.84 (172.59)	123.70 (172.92)	85.88 (139.62)	129.11 173.54)
Lake Trout	4.66 (6.00)	2.19 (3.08)	2.90 (4.59)	0.08 (0.16)
Chinook Salmon	1.05 (1.40)	4.81 (3.06)	2.72 (2.39)	3.63 (3.21)
Coho Salmon	2.71 (2.09)	0.49 (0.55)	4.00 (5.39)	0.51 (0.78)
Rainbow Trout	0.11 (0.14)	1.81 (2.61)	1.20 (1.28)	0.12 (0.21)
Catch Rate Index	6.81 (7.91)	5.78 (5.15)	2.92 (2.90)	2.00 (2.17)
Effective Toxins	0.60 (0.49)	2.27 (1.87)	3.46 (2.85)	2.27 (1.87)

Notes

a. Catch rates are measured here in terms of fish caught per person per 100 hours of effort. Standard deviations are reported below the averages. In the analysis below, the catch rates were rescaled to reflect catch rates per person per hour of effort.

Table 9.2: Site Selection Models

Variables	Linear-Indiv. Catch Rates (S1)	Linear-Catch Rate Index (S2)	Generalized Leontief- Catch Rate Index (S3)
$y-p$	227.25 (2.36)	277.03 (2.08)	-112.18 (10.58)
E	-0.17 (0.98E-2)	-0.11 (0.78E-2)	0.61 (0.08)
$R_{\text{lake trout}}$	-11.82 (0.53)		
$R_{\text{chinook salmon}}$	-20.58 (0.97)		
$R_{\text{coho salmon}}$	2.00 (0.54)		
$R_{\text{rainbow trout}}$	14.79 (1.47)		
R_I		8.12 (0.21)	-3.94 (0.69)
$\sqrt{y-p}$			337.25 (13.38)
$\sqrt{E}$			-3.76 (0.37)
$\sqrt{R_I}$			7.69 (0.73)
$\sqrt{(y-p)E}$			1.85 (0.33)
$\sqrt{(y-p)R_I}$			-2.91 (1.09)
$\sqrt{E \cdot R_I}$			-0.23 (0.12)
θ	1.47 (0.03)	1.00 (0.02)	0.84 (0.02)
log likelihood	-1822.71	-1766.33	-1639.84

Notes

a. Standard errors are in parentheses below the point estimates.

Table 9.3: Tobit Participation Models

Functional Form:	Linear			Generalized Leontief		
Site Selection Model Used to form the Index $\tilde{p}$:	Linear 4 Catch Rates (L1)	Linear Catch Rate Index (L2)	GL Catch Rate Index (L3)	Linear 4 Catch Rates (G1)	Linear Catch Rate Index (G2)	GL Catch Rate Index (G3)
Constant	-3.67* (1.46)	-5.38* (1.50)	-2.04 (2.11)	4.46 (7.85)	-11.00 (8.16)	7.48 (15.37)
y	0.33E-03 (0.42E-03)	-0.17E-02* (0.54E-03)	-0.22E-03 (0.18E-03)	0.16E-03 (0.02)	0.06* (0.01)	0.02* (0.99E-02)
$\tilde{p}$	0.38E-03 (0.49E-03)	-0.02* (0.66E-02)	-0.65E-03 (0.54E-03)	-0.65E-02 (0.03)	-0.79* (0.20)	-0.05* (0.03)
B	12.74* (1.40)	12.49* (1.38)	12.63* (1.39)	17.60* (6.04)	24.61* (5.94)	34.09* (11.11)

Functional Form:	Linear			Generalized Leontief		
Site Selection Model Used to form the Index $\tilde{p}$:	Linear 4 Catch Rates (L1)	Linear Catch Rate Index (L2)	GL Catch Rate Index (L3)	Linear 4 Catch Rates (G1)	Linear Catch Rate Index (G2)	GL Catch Rate Index (G3)
$\sqrt{y}$				1.54*	-0.75	-1.60*
				(0.77)	(0.83)	(0.95)
$\sqrt{-\tilde{p}}$				-1.74*	2.66	3.12*
				(0.86)	(2.98)	(1.70)
$\sqrt{y}\sqrt{-\tilde{p}}$				-0.61E-02	-0.44*	-0.07*
				(0.05)	(0.11)	(0.03)
$\sqrt{y}\sqrt{B}$				-1.00*	0.79	-0.37
				(0.51)	(0.52)	(0.24)
$\sqrt{-\tilde{p}}\ \sqrt{B}$				1.04*	-2.92	0.52
				(0.55)	(1.84)	(0.38)

Functional Form:	Linear			Generalized Leontief		
Site Selection Model Used to form the Index $\tilde{p}$:	Linear 4 Catch Rates (L1)	Linear Catch Rate Index (L2)	GL Catch Rate Index (L3)	Linear 4 Catch Rates (G1)	Linear Catch Rate Index (G2)	GL Catch Rate Index (G3)
σ	11.80* (0.58)	11.70* (0.57)	11.77* (0.57)	11.73* (0.58)	11.45* (0.55)	11.56* (0.56)
log likelihood	-1093.58	-1087.63	-1093.16	-1089.72	-1075.30	-1088.57

Notes

a. Standard errors are reported in parentheses below the coefficient estimates.

b. Significance at the 5% level is indicated by an asterisk next to the coefficient estimate.

Table 9.4 Kuhn-Tucker Model Estimates

Variables	Four Catch Rates (K1)	Aggregate Catch Rate (K2)
Constant	-9.38**	-9.14**
	(0.23)	(0.23)
$R_{\text{lake trout}}$	-0.70	
	(1.85)	
$R_{\text{chinook salmon}}$	13.53**	
	(2.31)	
$R_{\text{coho salmon}}$	5.65**	
	(1.57)	
$R_{\text{rainbow trout}}$	16.86**	
	(4.68)	
R_I		8.61**
		(1.02)
E	-0.06*	-0.07**
	(0.03)	(0.02)
B	1.17**	1.20**
	(0.14)	(0.16)
θ	1.45**	1.39**
	(0.20)	(0.19)
γ	1.32**	1.37**
	(0.05)	(0.06)
log likelihood	-1629.07	-1651.31

Notes

a. Standard errors are reported in parentheses below the coefficient estimates.

b. Significance at the 1% level is indicated by two asterisks next to the coefficient estimate and significance at the 5% level is indicated by a single asterisk..

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Table 9.5 Point Estimates of Welfare Reduction

Model	Variant	Units	Policy Scenario: Toxin Reduction	Coho Extinction	Loss of South Lake Michigan
Linked	L1	$/year	146.05	-116.95	-2404.14
	L2	$/year	-122.24	401.76	1515.30
	L3	$/year	0.74	42.23	235.16
	G1	$/year	-314.10	172.68	3148.33
	G2	$/year	-238.83	1011.86	2483.52
	G3	$/year	11.17	149.51	729.87
Site Selection	S1	$/choice	-70.75	38.24	724.06
	S2	$/choice	-3.05	8.20	37.12
	S3	$/choice	-0.47	37.12	27.55
Kuhn-Tucker	K1	$/year	-59.79	372.59	533.77
	K2	$/year	-73.82	400.55	583.03

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