VALUING WATER QUALITY IMPROVEMENTS USING REVEALED PREFERENCE METHODS WHEN CORNER SOLUTIONS ARE PRESENT*

by

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

Abstract

When valuing water resources using multiple site recreation data, it is typical to observe many corner solutions. We present as a benchmark a theoretical model of recreation choice when corners are present, and assess the degree to which several empirical specifications match the benchmark. As an illustration, we estimate and compare the repeated nested logit, a random parameters repeated nested logit, systems of demand, and Kuhn-Tucker models and use the results to value changes in water quality in the Wisconsin Great Lakes region.

July 1, 1998

---

* Daniel Phaneuf is an assistant professor in the Department of Agricultural and Resource Economics at North Carolina State University. Joseph Herriges and Catherine Kling are associate and full professors, respectively, in the Department of Economics at Iowa State University. We would like to thank Richard Bishop, Audrey Lyke, and Mike Welsh for providing us with data used in the analysis below and Kenneth Train for providing programs used in the estimation of the random parameters logit models.

Introduction

Revealed preference methods for valuing water quality improvements use observed behavior to indirectly value water resources. Particularly when valuing water resources for recreation purposes, it is typical to observe many corner solutions in the data. Corner solutions arise in multiple site data when consumers visit only a subset of the available recreation sites, setting their demand to zero for the remaining sites. While this phenomenon in the data is easily modeled from a theoretical perspective using Kuhn-Tucker conditions, it presents special challenges from an empirical perspective. Recently, Phaneuf, Kling, and Herriges and Herriges, Kling, and Phaneuf have addressed some of the estimation challenges associated with modeling corner solutions in recreation demand. A central theme in these papers has been to examine empirical models that are consistent with utility maximization theory. This paper continues this line of work. Specifically, we set up a general theoretical model of recreation choice to use as a benchmark, discussing the implications for empirical specification. Next, we examine three different empirical specifications, assessing the degree to which these models match the theoretical benchmark in their current form and how they might be adapted to better represent the theoretical model. Finally, we estimate each model using data on water based recreation in the Great Lakes region, providing and contrasting welfare estimates for changes in water quality.

Theoretical Model of Recreation Choice When Corner Solutions are Present

The model we adopt here has been called the quality differentiated goods model (Bockstael and McConnell) where demand for a commodity such as recreation depends on quality of the commodity as well as prices and income. We will treat this model as an “ideal” which will be used to assess alternative empirical recreation demand models. A consumer faced with a choice of alternative recreation sites to visit solves an optimization problem of the following form

$$\underset{x,z}{Max}\, U(\mathbf{x}, z, \mathbf{q}, \varepsilon^{\text{int}}) \quad s.t. \quad \mathbf{p}'\mathbf{x} + z = y, \quad x_j \geq 0, \quad j = 1, \ldots, M, \tag{1}$$

where **x** is a vector of visits to recreation sites, **p** is a vector of site prices, **q** is a vector of the corresponding qualities (assume site quality is a scalar for each site), ε^{int} is a vector of error terms that generates integer values for each item in the **x** vector[1], z is a numeraire, M is the total number of recreation sites and y is the consumer's income.

The solution to this problem can be characterized by Kuhn-Tucker conditions. Equivalently, a heuristic approach outlined in Bockstael, Hanemann, and Strand can be used to characterize the solution. The advantage to this latter approach is that it demonstrates more clearly the implications of the non-negativity constraints for model structure. The procedure is to break up the optimization in (1) into a series of conditional optimization problems, from which the unconditional optimum is chosen.

To begin with, note that there are 2^M possible combinations of nonzero subsets of the sites; that is, there are 2^M possible "corners" for the consumer to choose between. For each of these corners, a conditional maximization problem can be specified. The solution to the unconditional problem will be identically the solution to the conditional problem that yields the greatest utility. Let ω index the 2^M nonzero combinations of the sites (i.e., $\omega = 1, \ldots, 2^M$). Next, define a conditional maximization problem associated with each ω;

$$\underset{x,z}{Max}\, U(\mathbf{x}, z, \mathbf{q}, \varepsilon^{\text{int}}) \quad s.t. \quad \sum_{j \in \omega} p_j x_j + z = y \quad \text{and} \quad x_j = 0, \; j \notin \omega. \tag{2}$$

[1] Haab and McConnell present a model of count demand functions where they demonstrate the use of an error term to generate the count nature of the data.

The solution to this problem yields a set of Marshallian demands and an indirect utility function for each corner solution. Denote these functions as $\mathbf{x}_\omega = \mathbf{x}_\omega(\mathbf{p}_\omega, y, \mathbf{q}, \varepsilon^{\text{int}})$ and $\mathbf{V}_\omega = \mathbf{V}_\omega(\mathbf{p}_\omega, y, \mathbf{q}, \varepsilon^{\text{int}})$ respectively, where $\mathbf{p}_\omega = \{p_j : j \in \omega\}$ is the vector of prices for those commodities that have not been constrained to zero. Note that the conditional demand for x_i depends on its own price and the price of other goods in the constrained choice set ω, but *not* on the prices of goods constrained to zero. Thus, when the demand for x_j in the demand system is exactly zero, p_j does not enter the demand functions for the remaining n-1 goods. The presence of corner solutions changes the very structure of demand systems! This result is important for applied economists since it indicates that when one or several goods are not chosen, their prices drop out of the demand functions for the remaining chosen goods.

In general, the nonzero demands are functions of *all* of the qualities of *all* goods. However, if weak complementarity exists between visits to sites and their respective qualities, then the constrained demand and indirect utility functions associated with this problem can be simplified to $\mathbf{x}_\omega = \tilde{\mathbf{x}}_\omega(\mathbf{p}_\omega, y, \mathbf{q}_\omega, \varepsilon^{\text{int}})$ and $\mathbf{V}_\omega = \tilde{\mathbf{V}}_\omega(\mathbf{p}_\omega, y, \mathbf{q}_\omega, \varepsilon^{\text{int}})$. By definition, weak complementarity implies that utility does not change when the quality of an unvisited site changes. This means that when $x_j = 0$, the constrained utility level does not depend on q_j. Again, this has important implications for applied researchers. When researchers are specifying demand equations, it is inappropriate to include the quality of substitute sites when quality at those substitutes is thought to be weakly complementary.

The solution to the unconstrained problem can be recovered from the set of constrained problems by noting that the consumer will choose to visit that set of sites that yields the highest utility, i.e., $\mathbf{V}(\mathbf{p}, y, \mathbf{q}, \varepsilon^{\text{int}}) = \underset{\omega}{Max}\left\{\tilde{\mathbf{V}}(\mathbf{p}_{\omega}, y, \mathbf{q}_{\omega}, \varepsilon^{\text{int}})\right\}$. This characterization of the consumer's maximization problem as a two-stage process reveals the important properties of the recreation demand decision in a utility theoretic formulation. In assessing empirical models of recreation demand, the features of the theoretical solution can provide guidance regarding specification. Specifically, an accurately specified empirical model should:

- Model simultaneously the decisions of how often to visit a site and which subset of sites to visit in positive quantities.
- Model the number of visits to a given site as a function of its own price and prices of other visited sites. The number of visits should *not* depend upon the prices of unvisited sites.
- If weak complementarity is assumed, the number of visits to a site should depend upon the own quality, but not the qualities of unvisited sites.
- Specifically incorporate the integer (count) nature of the data in the model.

Although some empirical revealed preference models of recreation demand do incorporate some of these features, none of the models estimated to date incorporate all of them. In the next section, we briefly present three recreation demand models as they have been commonly estimated and assess the degree to which they capture the above mentioned features of the problem. We then discuss how each model might be adapted to more accurately incorporate these features.

Three Empirical Models

The three empirical models we investigate are (1) the repeated nested logit (RNL) model initiated by Morey, Rowe and Watson; (2) a system of demand equations such as those estimated by Burt and Brewer, Cichetti, Fisher, and Smith, and Ozuna and Gomez; and (3) a Kuhn-Tucker (KT) model (Phaneuf, Kling, and Herriges). We chose these three models because they each have a claim to being utility theoretic and they represent well the range of alternative empirical models analysts have implemented.

Repeated Nested Logit Model

The RNL model is based on the random utility framework attributable to McFadden. In this model, recreationists are assumed to choose the alternative (recreation site) that yields the highest utility on any given choice occasion. By specifying a particular utility function and an error distribution, the analyst forms probability statements concerning the likelihood of visiting a particular site on any given choice occasion which in turn form the basis for maximum likelihood estimation. The innovation of the RNL model is to include the decision not to visit a site on any given choice occasion as one of the alternatives. In this way, the choice of how many visits to take in a season is modeled as a series of independent decisions across all choice occasions.

The basic model proceeds by specifying a conditional indirect utility function associated with each alternative: $V_i = V_i(y_c - p_i, q_i) + \varepsilon_i$ (i=1,…,M), where y_c is the per choice occasion income. The utility associated with not taking a recreational trip on any given choice occasion is similarly specified as $V_0 = V_0(y_c) + \varepsilon_0$. On each choice occasion, the recreationist chooses whether to visit a recreation site and, if so, which site to visit, depending upon which of these alternatives yields the highest utility. The RNL typically nests the alternatives that include recreational visits separately from the no-trip alternative. Additional nesting of the visit alternatives may also be done.

Strictly speaking, the RNL model is consistent with utility theory in that it follows McFadden's random utility maximization (RUM) hypothesis. In addition, the structure of the model is consistent with the theoretical discussion in that only the price and quality of the chosen good enters the indirect utility function for each choice occasion. The integer nature of the data is accurately reflected in that the model provides count-data predictions of how many trips are made in a season and the number of visits to each site. Two well-known criticisms of the model, however, are that for estimation purposes a fixed number of choice occasions is assumed during the season and the individual's decision are assumed to be independent across choice occasions. While little can be done about the fixed number of choice occasions, recent developments in the use of the random-parameter logit model (RPL) (Train (1998a,b), McFadden and Train) provide a potential answer to the independence criticism.

The RPL generalizes a standard multinomial logit model by allowing coefficients to vary randomly rather than being fixed. The model begins like the standard MNL model, specifying that the utility received by individual *n* during choice occasion *t* from selecting alternative *i* is given by $V_{nit} = V(x_{nit}, \varepsilon_{nit}; \beta_{nt}) = \beta_{nt} x_{nit} + \varepsilon_{nit}$, where ε_{nit} is an iid extreme value disturbance term. The difference emerges from the fact that the parameter vector β_{nt} is not assumed to be constant for all *n* and *t*. Instead, the β_{nt}'s are treated as random parameters drawn from some distribution, known to the consumer but unobserved by the analyst. Train (1998b) suggests that correlation across choice occasions can be introduced in this framework by assuming that $\beta_{nt} = \beta_n \ \forall t$. Given this assumption, and conditional on the parameter vector β_n for individual *n*, the probability of observing individual *n*'s sequence of T choices is the product of the standard multinomial probabilities for each choice occasion:

$$Y_n(\beta_n) = \prod_{t=1}^{T} \frac{\exp(\beta_n x_{i(n,t)})}{\sum_j \exp(\beta_n x_j)}, \tag{3}$$

where $i(n,t) = 1$ if individual *n* chose alternative *i* on choice occasion *t*; = 0 otherwise. The unconditional probability (P_n) is obtained by integrating this product over all values of β; i.e.,

$P_n(\theta) = \int Y_n(\beta) f(\beta|\theta) d\beta$, where $f(\beta|\theta)$ is the assumed pdf for β, parameterized by θ. Finally, the log-likelihood function for all individuals in the sample is $L(\theta) = \sum_n \ln P_n(\theta)$. Simulation methods are then used to conduct maximum likelihood estimation of the θ's (See Train, 1998b).

There are several advantages of the RPL model over its MNL counterpart. First, it does not exhibit the restrictive "independence of irrelevant alternatives" property characteristic of MNL. Indeed, like nested logit, alternatives can be "grouped" together by introducing a dummy variable to the set of explanatory variables (i.e., the x_{nit}'s) identifying a specific collection (or nest) of alternatives. Second, the RPL model allows for wider variation in preferences, yielding an estimated distribution of the marginal impact of each explanatory variable (i.e., the x_{nit}'s). Finally, in a panel data setting, RPL allows for explicit correlation among choice occasions for a given individual. For these reasons, we propose combining the RNL and RPL models, yielding what we will refer to below as the random parameters, repeated nested logit, or RPRNL, model.

Systems of Demands

A second approach to estimating recreation demand when there are corner solutions present is to specify a system of demand equations (or share equations) and employ an estimator that explicitly accounts for the abundance of zeros. The specification and estimation of demand systems has a long history in applied economics and there have been a variety of applications in recreation demand. Recent studies have investigated estimators that account for censoring of the sample and/or the count nature of the data (e.g., Ozuna and Gomez; Morey, *et al*. (1995); and Shonkwiler). A system of demand equations can be specified in general form as

$$
\begin{aligned}
x_1 &= x_1(\mathbf{p},\mathbf{q},y) + \varepsilon_1 \\
\vdots \quad & \qquad \vdots \qquad\quad \vdots \\
x_M &= x_M(\mathbf{p},\mathbf{q},y) + \varepsilon_M .
\end{aligned}
\tag{4}
$$

Note that in this traditional specification of the system, each demand function is assumed to depend upon all prices and qualities, regardless of whether corner solutions are present. Typically, Tobit or other similar procedures are used to correct for the censoring of the dependent variable.

An adaptation of this basic systems model that incorporates the changes in demand function structure associated with corner solutions can be easily specified using a set of dummy variables. To illustrate, suppose there are only two demand functions in our system and that they are specified to be linear:

$$
\begin{aligned}
x_1 &= \alpha_1 + \beta_{11} p_1 + \beta_{12} d_2\, p_2 + \gamma_{11} q_1 + \gamma_{12}\, d_2 q_2 + \varepsilon_1 \\
x_2 &= \alpha_2 + \beta_{21} d_1 p_1 + \beta_{22}\, p_2 + \gamma_{21} d_1\, q_1 + \gamma_{22}\, q_2 + \varepsilon_2
\end{aligned}
\tag{5}
$$

where $d_i = 1$ if $x_i > 0$; $d_i = 0$ otherwise. Note that the specification in (5) imposes weak complementarity as well as the structural change that comes with corner solutions concerning prices.

Kuhn-Tucker Model

The Kuhn-Tucker (KT) model was originally proposed by Wales and Woodland as an estimation method for data with many binding non-negativity constraints, and has been recently applied in the recreation demand literature by Phaneuf, Kling, and Herriges. It begins with the maximization of a random utility function, which generates Kuhn-Tucker conditions that are also random. From these conditions probabilistic statements can be made regarding the observed outcome in the data. Formally the consumer solves

$$\begin{aligned} &\underset{x,z}{Max}\, U(\mathbf{x}, z, \mathbf{q}, \gamma, \varepsilon) \\ &s.t.\;\; \mathbf{p}'\mathbf{x} + z = y, \quad z \geq 0, x_j \geq 0,\; j = 1,.., M, \end{aligned} \tag{6}$$

where $U(\cdot)$ is assumed to be a quasi-concave, increasing, and continuously differentiable function of $(\mathbf{x}, z)$, $\varepsilon = (\varepsilon_1,...\varepsilon_M)'$ is a vector of random disturbances capturing the variation in preferences in the population, and **x**, **p**, **q**, and γ are as defined above. Given assumptions on the structure of the utility function, the standard Kuhn-Tucker conditions for utility maximization can be algebraically manipulated and conveniently expressed in the form[2]

$$\varepsilon_j \leq g_j(\mathbf{x}, y, \mathbf{p}, \mathbf{q}, \gamma);\;\; x_j \geq 0;\;\; x_j\left[\varepsilon_j - g_j(\mathbf{x}, y, \mathbf{p}, \mathbf{q}, \gamma)\right] = 0,\; j = 1,\ldots, M. \tag{7}$$

This form of the first order conditions, along with a specification of the density function $f(\varepsilon)$ for ε, provides the necessary information to construct the probability of the outcome in the data. For example, the probability of observing the first *k* goods consumed is given by

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

where J_k is the Jacobian transformation from ε to $(x_1,\ldots,x_k,\varepsilon_{k+1},\ldots,\varepsilon_M)'$. There are 2^M possible consumption patterns for which a probability as in (7) can be assigned. Each individual in the data is assigned a probability based on their observed visits, and maximum likelihood is used to recover estimates of the utility function parameters.

The Kuhn-Tucker model simultaneously predicts the number of trips made and which subset of sites is visited. The integrated behavioral and econometric model automatically enforces the theoretical constraints of the corners model, i.e. only prices of consumed goods enter the demand equations. As discussed in Herriges, Kling, and Phaneuf, however, the Kuhn-Tucker

[2] See Phaneuf, Kling, and Herriges for more detail on the derivation of the Kuhn-Tucker model.

model is still rather challenging to implement. Estimation becomes difficult with more than a small number of goods, and so far only relatively restrictive utility functions have been used in applications of the model. In addition, the integer nature of recreation data has not yet been addressed in the Kuhn-Tucker model.

Application

The focus of the empirical analysis is angling in the Wisconsin Great Lakes. The usage data come from two mail surveys of angling behavior conducted in 1990 at the University of Wisconsin-Madison.[3] 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). For this analysis, we have combined the destinations of Great Lakes anglers into four aggregate sites: Lake Superior, South Lake Michigan, North Lake Michigan, and Green Bay. The price of a trip to each of the fishing sites consists of both the direct cost of getting to the site (round trip travel cost) and the opportunity cost of the travel time (computed here as one third the wage rate, assuming an average travel speed of forty-five miles per hour).

To characterize the demand for trips to the fishing sites, we include in the empirical specifications two household characteristics and two measures of site quality. Household income is included, as well as a dummy variable to indicate ownership of a Great Lakes suitable boat. The two quality variables are fishing catch rates and toxin levels in lake trout flesh. For each site, a catch rate index is formed as the sum of the catch rates for four aggressively managed

[3] Details of the sampling procedures and survey design are provided in Lyke.

salmonoid species: lake trout, rainbow trout, Chinook salmon, and Coho salmon. Toxin levels in lake trout flesh are included in the empirical specifications for two reasons: toxins in fish flesh provide a good proxy for overall water quality, and are responsible for fish consumption advisories.[4]

Model Specifications

The estimation of the models identified above first requires the specification of the functional forms for both the stochastic and nonstochastic portions of each model. For the basic RNL model, the conditional indirect utilities per choice occasion for the four sites are specified as $V_j = \beta_1(y_c - p_j) + \beta_2 Catch_j + \beta_3 Toxin_j + \varepsilon_j$ (*j*=1…4). The indirect utility associated with not making a recreation trip is assumed to be $V_0 = \beta_0 + \beta_1 y_c + \beta_4 Boat + e_0$, where y_c is per choice occasion income and it is assumed that there are 50 choice occasions during the season. The stochastic elements are drawn from a Generalized Extreme Value distribution that yields a three-level nest. The first level is the binary choice of whether or not to make a trip, while the lower levels group the recreation sites, with North Lake Michigan and Green Bay in one nest and South Lake Michigan and Lake Superior in another.

The RPRNL analog proceeds similarly to the repeated nested logit. The utilities associated with visiting each site and not making a trip are the same with two exceptions. First, the stochastic terms are now distributed extreme value. Second, coefficients are assumed random. Here, we assume that $\beta_k \sim N\left(b_k, \sigma_k^2\right)$ (*k*=0,2,3,4). The marginal utility of income term (β_1) is assumed to be a constant across households.

The systems model takes a linear form analogous to equation (5) above, with the demand

[4] Details regarding the formation of both the catch rate and toxin variables are provide in Phaneuf.

for site *i* given by $x_j = \alpha_j + \beta_{jj} p_j + \sum_{k \neq j} \beta_{jk} d_k \, p_k + \gamma_{jj} q_j + \sum_{k \neq j} \gamma_{jk} d_k \, q_k + \varepsilon_j$ (*j*=1…4). The errors are assumed to be drawn from a truncated GEV distribution with the same nesting structure as in the RPL model.

Finally, the empirical KT model starts with the specification of the utility function as a version of the linear expenditure systems, with $U(\mathbf{x}, z, \mathbf{q}, \gamma, \varepsilon) = \sum_{j=1}^{4} \Psi_j(q_j, \varepsilon_j)\ln(x_j + \theta) + \ln(z)$, where $\Psi_j(q_j, \varepsilon_j) = \exp(\delta_0 + \delta_1 Catch_j + \delta_2 Toxins_j + \delta_3 Boat + \varepsilon_j)$ can be interpreted as a quality index for site *j*. Again, the errors are assumed to be drawn from a GEV distribution with the same nesting structure as in the RNL model.

Results

The Wisconsin Great Lakes Anglers survey provided the data for estimating recreation demand using the four models specified above; i.e., the RNL, RPRNL, KT, and systems models. The resulting parameter estimates themselves are not readily compared across the four models, with explanatory variables directly augmenting somewhat different aspects of consumer preferences. In the case of the RNL and RPRNL models, the conditioning variables directly impact the conditional indirect utility associated with each site, whereas in the systems model they directly impact the number of trips to a given site. Furthermore, space constraints prohibit the presentation of all the resulting parameters. However, to provide some flavor as to the performance of each of the models, Table 1 provides the estimates of select parameters, indicating the effects of the site attributes of price, catch rate, and toxin levels, as well as the consumer attribute of boat ownership.

All four specifications yield parameter estimates that are in line with expectations. Higher prices generally lead to a lower level of utility associated with a given site or reduction in the direct demand for that site. Likewise, higher catch rates enhance the desirability of a site and demand for recreation is higher for those that currently own a boat. However, the four models are less uniform in terms measuring the impact of toxins on recreation demand. The RNL, RPRNL and KT models find that toxins significantly reduce the utility or quality of a site. This is less clear, however, in the systems model. For sites 2 and 4, higher toxin levels reduce recreation demand (and significantly so in the case of site 4). However, toxins have a positive, though insignificant, effect on the remaining two sites.[5]

While the parameters of the four models are not directly comparable, they can each be used to evaluate the welfare effects of changes in water quality in the Great Lakes fishery, which can be compared. For each of the estimated models, the welfare effects of the following two hypothetical scenarios are examined:

- <u>Scenario A: 20% Reduction in Toxins at all Sites</u> Improved industrial and municipal waste management leads a general improvement of water quality at all sites, resulting in a decrease in toxin levels.

- <u>Scenario B: Loss of South Lake Michigan</u> Due to an environmental disaster, South Lake Michigan is no longer suitable for recreation fishing and is eliminated from the choice set.

Table 2 provides estimates of the compensating variation associated with each scenario for each of the models.[6] Not surprisingly, the four models yield a wide range of welfare estimates. In the case of toxins, the RPRNL, KT and RNL yield the expected welfare gain (i.e., a negative compensating variation) associated with reduced toxin levels. This is consistent with the parameter estimates provided in Table 1. All four models suggest that the loss of the South Lake Michigan site will substantially reduce consumer welfare, though the estimated compensating

[5] Another aspect of the RPRNL parameter estimates worth noting is that estimated variability in random parameters (i.e., σ_i 's) is statistically significant, implying significant correlation in site selection across choice occasions, a feature not captured by the basic RNL model.

[6] Details regarding the computation of the welfare measures are available from the authors upon request, as well as the complete estimation results for all four models.

variations range from a low of $98.34 in the RPRNL to a high of $849.09 in the case of the KT. One explanation for the larger welfare estimates from the KT model is that they contain non-use (but not existence) value, whereas the other models reflect only direct use value.

Conclusions

As mentioned above, each of these four approaches can claim in some sense to be utility theoretic. At this point it appears that the Kuhn-Tucker model comes closest to matching the ideal theoretical model developed in the first section. The relative difficulties associated with its use, however, may preclude its application in every situation. In contrast, the repeated nested logit is easy to implement, but relies on restrictive assumptions. Appealing, and worthy of additional research beyond this presentation, is the use of random parameter logit as an analog to the repeated nested logit model. Likewise, systems of demand equations that account for the structural changes associated with corners are worthy of further research given their relative ease of estimation and ability to apply using flexible functional forms.

References

Bockstael. N.E., W.M. Hanemann, and I.E. Strand. "Benefit Analysis Using Indirect or Imputed Market Methods," Volume II, "Measuring the Benefits of Water Quality Improvements Using Recreation Demand Models," EPA Cooperative Agreement CR-811043-01-0 (1986).

Bockstael, N. E. and K.E. McConnell. “Public Goods as Characteristics of Non-market Commodities,“ *The Economics Journal* **103**(1993): 1244-1257.

Burt, O.R. and D. Brewer. "Estimation of Net Social Benefits from Outdoor Recreation," *Econometrica* **39**(1971): 813-231.

Cichetti, C., A. Fisher, and V. Smith. "An Econometric Evaluation of a Generalized Consumer Surplus Measure: The Mineral King Controversy," *Econometrica* **44**(1976):1259-1276.

Haab, T.C. and K.E. McConnell. "Count Data Models and the Problem of Zeros in Recreation Demand Analysis," *American Journal of Agricultural Economics* **78**(1996): 89-102.

Herriges, J.A., C.L. Kling, and D.J. Phaneuf, “Corner Solution Models in Recreation Demand: A Comparison of Competing Frameworks,“ forthcoming in J. A. Herriges and C. L. Kling (eds.) *Valuing the Environment Using Recreation Demand Models*, Aldershot: Edward Elgar Publishing Ltd.

Lyke, A. J., *Discrete Choice Model to Value Changes in Environmental Quality: A Great Lakes Case Study*, Ph.D. dissertation, Department of Economics, University of Wisconsin-Madison (1993).

McFadden, D. and K.E. Train, “Mixed MNL Models for Discrete Response,“ Department of Economics working paper, Univesity of California, Berkeley, 1997.

Morey, E.R., R.D. Rowe, and M. Watson. "A Repeated Nested-Logit Model of Atlantic Salmon Fishing," *American Journal of Agricultural Economics* **75**(August, 1993): 578-592.

Morey, E., D. Waldman, D. Assane, and D. Shaw. “Searching for a Model of Multiple-Site Recreation Demand that Admits Interior and Boundary Solutions,“ *American Journal of Agricultural Economics* **77**(1995): 129-140.

Ozuna, T., and I. Gomez. “Estimating a System of Recreation Demand Functions Using a Seemingly Unrelated Poisson Regression Approach,“ *Review of Economics and Statistics* (1994).

Phaneuf, D.J., *Generalized Corner Solutions in Recreation Demand*, Ph.D. dissertation, Department of Economics, Iowa State University (1997).

Phaneuf, D.J., C.L. Kling, and J.A. Herriges. “Estimation and Welfare Calculations in a Generalized Corner Solution Model with an Application to Recreation Demand,“ draft manuscript, Iowa State University, (1998).

Shonkwiler, J. S., “Recreation Demand Systems for Multiple Site Count Data Travel Cost Models,” forthcoming in J. A. Herriges and C. L. Kling (eds.) *Valuing the Environment Using Recreation Demand Models*, Aldershot: Edward Elgar Publishing Ltd. (1998).

Train, K.E., “Recreation Demand Models with Taste Differences Over People,“ forthcoming in *Land Economics*, 1998a.

Train, K.E. “Mixed Logit Models for Recreation Demand,“ forthcoming in J. A. Herriges and C. L. Kling (eds.) *Valuing the Environment Using Recreation Demand Models*, Aldershot: Edward Elgar Publishing Ltd. (1998b)

Wales, T.J. and A.D. Woodland, “Estimation of Consumer Demand Systems with Binding Non-Negativity Constraints,“ *Journal of Econometrics* **21**(1983): 263-285.

Table 1: Key Parameter Estimates

	Parameter Estimates							
	RNL	RPRNL		KT	System			
Variable		Mean	Std. Dev.		Site 1	Site 2	Site 3	Site 4
Price[a]	-0.003**	-0.01**	na	na	-0.04**	0.00	-0.02	-0.05**
	(0.000)	(0.00)			(0.01)	(0.01)	(0.02)	(0.01)
Catch Rate	1.99**	14.40**	24.07**	7.11**	29.63**	50.80**	25.81**	99.34**
	(0.07)	(0.87)	(0.74)	(0.81)	(4.98)	(8.39)	(23.31)	(10.00)
Toxin	-0.05**	-0.93**	0.97**	-0.07**	1.36	-0.16	0.14	-4.19**
	(0.00)	(0.04)	(0.03)	(0.02)	(1.28)	(0.23)	(0.31)	(1.58)
Boat	-1.55**	-1.42**	0.15	1.36**	1.44	6.35**	6.19**	10.21**
	(0.01)	(0.14)	(0.18)	(0.21)	(1.48)	(1.52)	(1.89)	(1.55)

[a]In the case of the systems model, price refers to the own price. For the RNL and RPRNL models, the price coefficients correspond to the negative of β_1.

**Statistically different from zero at a 99 percent confidence level.

Table 2: Welfare Estimates

	RNL	RPRNL	KT	System
Scenario A: 20% reduction in toxins	-29.16	-8.78	-116.45	10.99
Scenario B: Loss of South Lake Michigan	162.67	98.34	849.09	309.21