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Generalized corner solution models in recreation demand

by

Daniel James Phaneuf

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

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für Silke

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ABSTRACT

When examining consumer behavior using household level data, it is typical in many applications to find that consumers consume only a subset of the available goods, setting their demand to zero for the remaining goods. Examples of this include labor supply and food demand, as well as the demand for recreation. In multiple site recreation demand data sets, one usually observes that individuals visit only a subset of the available recreation sites, yet visit these sites multiple times during a season. Theoretically, these *corner solutions* are effectively modeled using non-negativity constraints in the utility maximization problem. Empirically estimating such a model is more challenging however, since most econometric techniques rely on the assumption of an interior solution.

This dissertation examines estimation of generalized corner solution models of consumer choice as they apply to recreation demand. The emphasis is on providing utility consistent characterizations of the demand for recreation, which can then be used to perform welfare analysis. Specifically, the Kuhn-Tucker model of Wales and Woodland (1983) and the dual approach of Lee and Pitt (1986) are estimated for a four site recreation model. Welfare measurement techniques are developed for each, relying on Monte Carlo integration to arrive at consistent estimates of the compensating variation associated with changes in site attributes or the elimination of a site.

The application focuses on the demand for fishing in the Wisconsin Great Lakes region. Data is available describing angler behavior during the 1989 fishing season, including both users and non-users of the Great Lakes fishery. Variables describing catch rates for the major sport fishing species, as well as pollution levels in the lakes, are

included in the estimation. Welfare experiments are conducted by analyzing the effects of hypothetical changes in the quality variables.

This research will be of interest not only to those working in recreation demand and resource valuation, but also those working in other areas of consumer choice, where the use of household level data is becoming more prevalent and operational methods for dealing with corner solutions are necessary.

CHAPTER 1: INTRODUCTION

Accurate measures of economic values of non-market environmental goods are important for policy makers as they attempt to evaluate competing uses of natural resources. Revealed preference models of the demand for environmental services, known as "travel cost models" or "recreation demand models", represent one method for estimating these values. Travel cost models of recreation demand use observed behavior to indirectly infer values of recreation opportunities and welfare effects of changes in recreation site characteristics. The price of the environmental good, a "trip" to a site in most models, is the cost of getting to the site and any on-site expenses. Many models also include the opportunity cost of time as part of the price. Once the demand for the resource is characterized, values of the environmental goods or the welfare effects of changes in the quality of the goods can be obtained using a variety of welfare measurement techniques.

The original work in recreation demand can be broadly divided into two areas: continuous demand models, in which a demand curve is estimated for a single recreation site, and discrete choice models based on the work of McFadden, where the random utility framework is employed to analyze the decision of which of several recreation sites to visit.[1] These models often employ the same type of data; it is in the approach to analyzing the recreation decision and the resulting welfare measures that they differ. In continuous demand models the demand curve for a site is estimated as a function of price, income,

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[1] Kling and Crooker (1997) provide a synopsis of the historical development of travel cost models.

and variables describing the quality of the recreation site. Consumer surplus measures are then used to arrive at the total value of the site, or the welfare effects of a shift in the demand curve caused by a change in an attribute of the site. A few examples of works pertaining to the continuous demand approach include Brown and Nawas (1973), Hellerstein (1995), Haab and McConnell (1996), Hellerstein and Mendelsohn (1993), and Kling (1989). Freeman (1993) and Bockstael, McConnell, and Strand (1991) provide valuable reviews.

A drawback of the single site framework has been the difficulty of effectively modeling prices and quality attributes of potential substitute sites. This has led to the development of random utility maximization (RUM) models to analyze the discrete choice of which of several recreation sites to visit on a given choice occasion. In these models the individual visits the site that provides the highest choice-occasion utility. The probability that a particular site is chosen is a function of the difference between utilities associated with the choice of each site and their random components. These models have been estimated using multinomial logit, nested logit, and to a lesser extent, probit. Using the concepts outlined in Small and Rosen (1981) and Hanemann (1984a), per choice occasion welfare measures can be obtained for changes in site characteristics or the elimination of a site. Examples of the use of random utility models in recreation demand include Hanemann (1978) and Caulkins, Bishop, and Bouwes (1986). Kaoru, Smith, and Liu (1995), Parsons and Kealy (1992), Herriges and Kling (1996,1997), and Kling and Herriges (1995) have examined some of the econometric issues surrounding the use of random utility models. Reviews are provided by Freeman (1993) and Bockstael,

McConnell, and Strand (1991). Morey (1998) provides an excellent discussion of the use of nested logit in recreation demand.

As with the continuous demand model, the early random utility models are not without their drawbacks. We are typically interested in the total values associated with a recreation site, yet the discrete choice models provide an estimate of the per choice occasion value. It is not clear how to aggregate single visit welfare measures to a seasonal or total measure. In addition, most individuals make several recreation decisions per year. Random utility models do not address the "how many trips to make" aspect of the recreation decision.

The discussion of the difficulties associated with the use of the early continuous demand and discrete choice travel cost models hints at a larger issue in recreation demand in particular and consumer choice situations in general. It is typical in many applications using household level data to find that consumers consume only a subset of the available goods, setting their demand for the remaining goods to zero. Examples of this include labor supply (Ransom, 1987a,b; Lacroix and Fortin ,1992; Fortin and Lacroix ,1994), and food demand (Wales and Woodland, 1983; Yen and Roe ,1989). In multiple site recreation data sets, one usually observes that individuals visit only a subset of the available sites, yet visit these sites multiple times during a season. Continuous demand models, discrete choice models, and traditional consumer choice models which rely on the assumption of an interior solution have not proven adept at addressing the prevalence of *corner solutions* in these data sets. Models are needed that address both the discrete component of the recreationist's decision (which sites to visit) and the continuous

component (how many trips to make in a season).

The purpose of this dissertation is to examine general corner solution models of consumer choice as they apply to recreation demand. Although the emphasis is on recreation demand, the methodology discussed is relevant to a wide range of consumer choice problems for which household level data is employed. Two broad strategies have emerged for dealing with such corner solutions. The first approaches the problem from a statistical perspective, relying on Amemiya's (1974) generalization of Tobin's (1958) limited dependent variable model to allow non-consumption of a subset of available goods in an econometric model. A modified version of this approach, known as the linked site selection and participation model, is relatively well established in the recreation demand literature (see for example Bockstael, Hanemann, and Kling (1987) and Hausman, Leonard, and McFadden (1995). Morey, Rowe, and Watson (1993) provide a related but somewhat different approach).

The second approach, dubbed the Kuhn-Tucker model by Wales and Woodland (1983), takes a more structural and utility theoretic approach, beginning the analysis with the maximization of a utility function. This has subsequently been extended to a dual form, beginning with the specification of an indirect utility function. Morey, Waldman, Assane, and Shaw (1995) suggest that the Kuhn-Tucker method is the preferred approach to the corner solution problem, yet due to the complexity of the model there have been few applications of the method to date (Wales and Woodland, 1983; Lee and Pitt, 1986b, 1987; Srinivasan and Winer, 1994; Ransom, 1987a,b) and none published in the

area of recreation demand.[2] Furthermore, little attention has been paid to the problem of welfare analysis within the context of the Kuhn-Tucker or dual models. This dissertation contributes the first applications of the Kuhn-Tucker and dual models to the problem to recreation demand, modeling the demand for fishing in the Wisconsin Great Lakes region. A methodology is developed and applied for estimating the compensating variation associated with changes in site characteristics, relying on Monte Carlo integration to derive expected welfare changes. The results from these efforts are compared with results from the established approaches.

The remainder of the dissertation is organized as follows: Chapter 2 reviews literature concerned with the two above mentioned approaches to solving the corner solution problem in consumer choice analysis. The theory behind the competing approaches in laid out in the process of the review. The Kuhn-Tucker and dual models for estimation are developed in Chapter 3. Chapter 4 reviews in detail the data available for the study, and Chapter 5 presents estimation and welfare calculations for both methods. Summary and conclusions are presented in Chapter 6.

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[2] Morey, Waldman, Assan, and Shaw (1990) present estimates in a working paper of a generalized corner solution model using the related Amemiya-Tobin approach for data on visits to recreation sites, though they do not develop methods for welfare analysis. Bockstael, Hanemann, and Strand (1986) suggest an empirical specification for a Kuhn-Tucker model without estimation.

CHAPTER 2: REVIEW OF CORNER SOLUTION THEORY

In the following sections, the linked site selection and participation, repeated nested logit, Kuhn-Tucker, and dual models are reviewed. The theory behind the models is presented, and the relative strengths and weaknesses of each approach are discussed.

2.1 The Linked Site Selection and Participation Models

The recreation demand literature has largely approached the corner solution problem by statistically linking site selection and participation models. The linked model was originally developed by Bockstael, Hanemann, and Strand (1986) and Bockstael, Hanemann, and Kling (1987) and has been subsequently modified and applied by Hausman, Leonard, and McFadden (1995), Feather, Hellerstein, and Tomasi (1996), Parsons and Kealy (1995), and Creel and Loomis (1992). Although these works differ slightly, they share the basic model design of examining the recreation decision in two steps. In the first step a random utility model is employed to determine the allocation of trips to available sites based on site characteristics and costs. In the second step the total number of trips is estimated using a regression of trips on individual characteristics and a price and/or quantity index, computed from the results of the first step.

Formally the linked model begins with the specification of a discrete choice RUM model. An individual is assumed to receive utility from choosing to visit site j ($j=1,...,J$) on a given choice occasion. Utility is received according to a conditional indirect utility function

$$U_j = V_j + \varepsilon_j,$$
(2.1)

where

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

is the non-stochastic component of indirect utility, p_j is the cost of visiting the site,

$\mathbf{q}_j = (q_{j1}, ..., q_{jk})'$ is a vector of site attributes, and ε_j is a random error term capturing

unobserved variation in preferences across individuals. On a given choice occasion the

individual is assumed to visit the recreation site that provides the greatest utility. The

probability that site j is chosen is given by

$$\pi_j = \Pr(V_j + \varepsilon_j > V_k + \varepsilon_k \ \forall k \neq j).$$
(2.2)

Specification of the distribution of the error vector $\varepsilon = (\varepsilon_1, ..., \varepsilon_J)'$ determines

which of the standard site selection models result. Typically the linked models have

employed either multinomial logit or nested logit. If it is assumed that ε is drawn from a

generalized extreme value distribution the model is nested logit, requiring the analyst to

group the available alternatives into nests of similar sites. This provides a means for

relaxing the independence of irrelevant alternatives assumption. Given that the model is

nested logit, the probability in equation (2.2) can be expressed as

$$\pi_j = \frac{e^{V_j/\theta_{n(j)}} \left[\sum_{i \ni n(i) = n(j)} e^{V_i/\theta_{n(j)}} \right]^{(\theta_{n(j)} - 1)}}{\sum_{m=1}^{N} \left[\sum_{k \ni n(k) = m} e^{V_k/\theta_m} \right]^{\theta_m}},$$
(2.3)

where $n(j)$ is an index function that equals m ($m=1, ..., M$) if site j has been assigned to nest

m, N denotes the total number of nests, and θ_m ($m=1,...,$N) is a parameter known as the dissimilarity coefficient, measuring the degree of similarity between sites within nest m (McFadden, 1981). Given a functional form for the utility functions a likelihood function is constructed by assigning a probability as in equation (2.3) to each choice occasion in the sample and taking the product. Maximum likelihood is used to recover estimates of the utility function and error distribution parameters.

The site selection model allows the construction of the inclusive value, which can be interpreted as a measure of the expected maximum utility from the site characteristics. The inclusive value is defined as

$$I = I(y, \mathbf{p}, \mathbf{q}) = \ln\left(\sum_{m=1}^{N}\left[\sum_{k \ni n(k)=m} e^{V(y-p_k, q_k)/\theta_m}\right]^{\theta_m}\right),$$ (2.4)

where $\mathbf{p} = (p_1,...,p_J)'$ and $\mathbf{q} = (\mathbf{q}_1,...\mathbf{q}_J)'$. If the specification of the conditional indirect utility function in equation (2.1) is linear in income, the *per choice occasion* compensating variation associated with a change in prices or site quality measures has a closed form expression, given by

$$C = \frac{1}{\beta_y}\left[I(y, \mathbf{p}^0, \mathbf{q}^0) - I(y, \mathbf{p}^1, \mathbf{q}^1)\right],$$ (2.5)

where the subscripts on the price and quality variable are used to distinguish the new and original levels, and β_y is the marginal utility of income (Small and Rosen, 1981). If the utility function is not specified as linear in income, there is no closed form for compensating variation, and numerical methods must be used (see McFadden, 1996;

Herriges and Kling, 1997).

As noted above the site selection model delivers a per-choice-occasion measure of the compensating variation associated with a change in site characteristics. If the total number of trips (T) taken by an individual is unaffected by this change, then the total compensating variation is C·T. It is a restrictive assumption, however, to assume that T remains unchanged. The second component of the linked model is designed to capture possible changes in the participation decision. A general form of the participation equation is given by

$$T = h(\mathbf{L}, \mathbf{c}, Y) + \mu, \tag{2.6}$$

where **L** is a vector of variables linking the participation equation to the site selection equation, **c** is a vector of other explanatory variables thought to influence the number of trips taken, Y is annual income, and μ is a random error term. The various applications of the linked model differ in how they specify the participation equation and how they conduct welfare analysis. Bockstael, Hanemann, and Kling (BHK, 1987) use the inclusive value computed in (2.4) as an explanatory variable, interpreting it as a probability weighted index of the value of the different alternatives. The participation equation therefore is

$$T = h_1(I, \mathbf{c}, Y) + \mu. \tag{2.7}$$

To compute the overall welfare measure, BHK suggest estimating the per-choice-occasion welfare measure $(\hat{C})$ from equation (2.5) and multiplying this by the number of trips predicted by (2.7), computed at the new level of prices and qualities. That is,

$$W_1 = \hat{C} \cdot \hat{h}_1(\hat{I}(y, \mathbf{p}^1, \mathbf{q}^1), \mathbf{c}, Y). \tag{2.8}$$

A variation on W_1 suggested by Creel and Loomis (1992) calculates total welfare as the product of predicted trips and the monetized welfare per trip (I / β_y). The corresponding welfare naturally becomes

$$W_1' = \frac{\hat{I}^0 \hat{h}_1^0}{\hat{\beta}_y} - \frac{\hat{I}^1 \hat{h}_1^1}{\hat{\beta}_y}, \tag{2.8'}$$

where $\hat{I}^0$ is the predicted value of the inclusive value at the original prices and qualities and $\hat{I}^1$ is the predicted value at the new prices and quantities.

Parsons and Kealy (PK, 1995) and Feather, Hellerstein, and Tomasi (FHT, 1995) offer a second variation for the participation equation. The estimated probabilities associated with the alternatives from the site selection model are used to compute the "expected price" of a trip and the "expected quality" of a trip. The expected price $\bar{P}$ for each individual is the sum of the individual's travel costs for each site weighted by the estimated probabilities of visiting each site. Each element of the expected quality vector $\bar{\mathbf{q}} = (\bar{q}_1, \ldots, \bar{q}_K)'$ is similarly computed as the sum of the those quality attributes for each site, weighted by the estimated probabilities of visiting each site. The participation equation is therefore

$$T = h_2(\bar{P}, \bar{\mathbf{q}}, Y) + \mu. \tag{2.9}$$

The welfare measurement used by FHT is similar to BHK. Parsons and Kealy, however, interpret the participation equation as an approximation to the demand curve, integrating under it with respect to price to produce estimates of changes in consumer surplus

resulting from quality or price changes. The welfare change associated with the improvement in a single site attribute would be computed as

$$W_2 = \int_{\overline{p}^0}^{\overline{p}^1} \hat{h}_2(p, \overline{q}^0, Y)dp + \int_{\overline{q}^0}^{\overline{q}^1} \hat{h}_2(\overline{p}^1, q, Y)dq, \tag{2.10}$$

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

The final variant on the linked model is from Hausman, Leonard, and McFadden (HLM, 1995), who propose a combination of the two approaches above. The participation stage is specified as

$$T = h_3(\widetilde{P}, \mathbf{c}, Y) + \mu, \tag{2.11}$$

where

$$\widetilde{P} = \frac{-I(y, \mathbf{p}, \mathbf{q})}{\beta_y} \tag{2.12}$$

is the negative of the per-choice-occasion consumer surplus . HLM interpret this as a price index, and argue that the two stages are a utility-consistent two-stage budgeting process. Equation (2.11) is the first stage, in which the consumer decides what to spend on recreation, while the site selection model represents the second stage allocation of the budget among the recreation goods. Given the validity of the two-stage budgeting process, to be further addressed below, equation (2.11) can be viewed as a demand curve. Integrating under it with respect to price yields theoretically sound welfare measures for changes in price or quality attributes.

The linked models have dominated the recreation demand literature because they have many attractive features. The presence of corner solutions is dealt with in an intuitively appealing manner, explicitly accounting for both the discrete and continuous nature of the recreation decision. Standard econometric techniques are used so the models are easy to estimate. More importantly, given the ability of multinomial logit and nested logit to handle large numbers of alternatives, many sites can be modeled without having to aggregate the data into small numbers of grouped sites, preserving the uniqueness of the choices. This feature is particularly attractive when recreation destinations are geographically distributed in a way that prevents destinations with similar characteristics from being grouped into logical aggregate sites. In spite of these advantages, however, the linked models exhibit several weakness. With the exception of HLM, the authors readily acknowledge that their models are not utility-theory consistent, but rather represent an intuitive approximation to the utility maximization process. Smith (1997) and Herriges, Kling, and Phaneuf (1997) point out that the HLM proof of utility consistency relies on an assumption which does not hold in general. Therefore, the analyst applying the linked model must choose between several specifications for the participation stage and welfare measures, none of which are derived from a utility theoretic framework. In addition, specifying two models to be estimated to explain a single agent's behavior leads to two problems. First, different explanatory variables are contained in the site selection and participation equations, while intuitively both components of the decision would depend on the same set of variables. Second, information is lost econometrically by estimating the two equations separately. Efficiency could be gained by accounting for the

likely correlation between error terms resulting from each component of the recreation decision.

Two final issues with the linked models relate to concerns in general with discrete choice models. First, for estimation purposes each choice occasion is an observation, implying that choice occasions across individuals are independent. This is necessary for construction of the likelihood function, but unlikely to be true in practice. Second, the ease of estimation and welfare calculation in the RUM model depends on the error distribution assumption and structure of the utility function. If the errors are assumed to be drawn from a normal distribution rather than the extreme value or generalized extreme value, the probit model results, requiring the evaluation of multidimensional normal integrals for estimation. Assuming the utility function is linear in income provides a closed form for compensating variation; assuming the utility function is non-linear in income, however, requires the use of computer intensive numerical methods to evaluate welfare changes. Improved simulation methods and econometric advances, and the availability of ever faster computers, have lessened the burden of these generalizations. Nonetheless, most applications of the linked model have used relatively restrictive error distributions and functional forms for utility.

2.2 The Repeated Nested Logit Model

Morey, Rowe, and Watson (MRW, 1993) suggest an alternative to the linked models that is still in the spirit of statistically linking the two components of the recreation decision. It is assumed that the recreation season can be divided into a fixed number of choice occasions (S) during which the individual can make either 0 or 1 trips. MRW

assume $S=50$, allowing the possibility of roughly one recreation trip per week. It is also assumed that all choice occasions are independent, including choice occasions for the same individual. Given these assumptions the participation and site selection decisions are modeled as an extension of the site selection model. That is, for a given choice occasion the individual faces $J+1$ alternatives: visiting one of J available recreation sites, or choosing not to visit any. The utility for alternative j on choice occasion s is given by

$$U_{js} = V_{js} + \varepsilon_{js}, \quad j = 0,1,...,J. \tag{2.13}$$

Choosing alternative $j=0$ implies a choice of not visiting a recreation site. If it is assumed the errors $\varepsilon = (\varepsilon_{0s},...,\varepsilon_{Js})'$ are distributed independently across choice occasions and individuals as generalized extreme value variates, the standard nested logit model results. The upper nest is the binary choice of whether or not to take a recreation trip, while the remaining nests distinguish which sites are visited if they choose to make a trip. The MRW approach is appealing in that, given the two assumptions above, it addresses the corner solution problem in a manner consistent with random utility maximization theory. It is easy to implement, using standard techniques for both model estimation and welfare calculations. As Morey, et al. (1995) point out however, the assumptions driving the model are not likely to hold. The number of choice occasions must be determined exogenously and be the same for all individuals. The assumption of independence of choice occasions across individuals is also questionable, precluding habit formation or learning from past experiences.

The Kuhn-Tucker Model

The Kuhn-Tucker model was first proposed by Wales and Woodland (1983) as an alternative to the Amemiya-Tobin limited dependent variable approach for data sets containing a significant number of corner solutions. Generalizing from Wales and Woodland's description, it begins with the assumption that consumer preferences over a set of $M+1$ alternatives can be represented by a random utility function, which they maximize subject to a budget constraint and a set of non-negativity constraints. Formally, each consumer solves

$$\underset{\mathbf{x},z}{Max}\, U(\mathbf{x},z,\mathbf{q},\gamma,\varepsilon) \tag{2.14}$$

such that

$$\mathbf{p'x} + z \le y \tag{2.15a}$$

and

$$z \ge 0, x_j \ge 0, j = 1,...,M, \tag{2.15b}$$

where $U(\cdot)$ is assumed to be a quasi-concave, increasing, and continuously differentiable function of $(\mathbf{x},z)$, $\mathbf{x} = (x_1,...,x_M)'$ is a vector of goods to be analyzed, z is the numeraire good, $\mathbf{p} = (p_1,...,p_M)'$ is a vector of commodity prices, y denotes income, and $\varepsilon = (\varepsilon_1,...,\varepsilon_M)'$ is a vector of random error terms capturing the variation in preferences in the population. The error vector is assumed to be known by the individual but unobserved by the analyst. The vector $\mathbf{q} = (q_1,...,q_K)'$ represents attributes of the M commodities.

The first order necessary and sufficient Kuhn-Tucker conditions for utility maximization are given by

$$U_j(\mathbf{x}, z; \mathbf{q}, \gamma, \varepsilon) = \frac{\partial U(\mathbf{x}, z; \mathbf{q}, \gamma, \varepsilon)}{\partial x_j} \leq \lambda p_j,$$

$$x_j \geq 0, \; x_j U_j(\mathbf{x}, z; \mathbf{q}, \gamma, \varepsilon) = 0, \quad j = 1, \dots, M, \tag{2.16a}$$

$$U_z(\mathbf{x}, z; \mathbf{q}, \gamma, \varepsilon) = \frac{\partial U(\mathbf{x}, z; \mathbf{q}, \gamma, \varepsilon)}{\partial z} \leq \lambda, \; z \geq 0, \; z U_z(\mathbf{x}, z; \mathbf{q}, \gamma, \varepsilon) = 0, \tag{2.16b}$$

and

$$\mathbf{p'x} + z \leq y, \; \lambda \geq 0, \; (y - \mathbf{p'x} - z)\lambda = 0, \tag{2.16c}$$

where λ denotes the marginal utility of income. For simplicity it is assumed that the numeraire good is a necessary good, so that equation (2.16b) can be replaced by

$$\lambda = U_z(\mathbf{x}, z; \mathbf{q}, \gamma, \varepsilon). \tag{2.16b'}$$

In addition, since $U(\cdot)$ is increasing in $\mathbf{x}$ and z the budget will be exhausted, implying

$$z = y - \mathbf{p'x}. \tag{2.16c'}$$

Substituting equation (2.16b') and (2.16c') into (2.16a) yields the M first-order conditions associated with the commodities of interest:

$$U_j(\mathbf{x}, y - \mathbf{p'x}; \mathbf{q}, \gamma, \varepsilon) \leq p_j U_z(\mathbf{x}, y - \mathbf{p'x}; \mathbf{q}, \gamma, \varepsilon),$$

$$x_j \geq 0, \tag{2.16a'}$$

$$x_j [U_j - U_z p_j] = 0, \; j = 1, \dots, M.$$

Finally, it is assumed that the utility function is defined such that $U_{z\varepsilon} = 0$, $\partial U_j / \partial \varepsilon_k = 0 \; \forall \; k \neq j$, and $\partial U_j / \partial \varepsilon_k > 0$, $j = 1, \dots, M$, so that

$$U_j(\mathbf{x}, y - \mathbf{p'x}; \mathbf{q}, \gamma, \varepsilon) = U_z(\mathbf{x}, y - \mathbf{p'x}; \mathbf{q}, \gamma, \varepsilon) p_j, \; j = 1, \dots, M, \tag{2.17}$$

defines a set of implicit equations for the ε_i's of the form

$$\varepsilon_j = g(\mathbf{x}, y, \mathbf{p}; \mathbf{q}, \gamma), \, j = 1, \ldots, M. \tag{2.18}$$

The first order conditions in (2.16a') can then be rewritten as

$$\varepsilon_j \leq g_j(\mathbf{x}, y, \mathbf{p}; \mathbf{q}, \gamma), \, x_j \geq 0, \, x_j g_j(\mathbf{x}, y, \mathbf{p}; \mathbf{q}, \gamma) = 0, \, j = 1, \ldots, M. \tag{2.19}$$

Equation (2.19), along with the specification of the joint density function $f_\varepsilon(\varepsilon)$ for ε, provides the necessary information to construct the likelihood function for estimation of the parameters. Consider an individual who chooses to consume positive quantities for only the first k commodities (i.e. $x_j > 0, \, j = 1, \ldots, k$ and $x_j = 0, \, j = k+1, \ldots, M$). Their contribution to the likelihood function is given by the probability

$$\int_{-\infty}^{g_{k+1}} \cdots \int_{-\infty}^{g_M} f_\varepsilon(g_1, \ldots, g_k, \varepsilon_{k+1}, \ldots, \varepsilon_M) \, abs|J_k| \, d\varepsilon_{k+1} \cdots d\varepsilon_M \tag{2.20}$$

where J_k denotes the Jacobian for the transformation from ε to $(x_1, \ldots, x_k, \varepsilon_{k+1}, \ldots, \varepsilon_M)'$. There are 2^M possible patterns of binding non-negativity constraints for which a probability statement such as (2.20) can be constructed. The likelihood function can then be formed as the product of the appropriate probabilities and maximum likelihood used to recover estimates of the utility function parameters.

Wales and Woodland (1983) apply the Kuhn-Tucker method to the demand for meat consumption in Australia using a Stone-Geary utility function, without including a numeraire good. Spending on three broad classes of meat products is analyzed, implying there are seven possible consumption patterns, or *demand regimes*. The model is used to demonstrate the marginal effects of demographic variables on expenditures for each product class, conditional on the observed demand regime. Morey, Waldman, Assane,

and Shaw (1990) provide an application of the related Amemiya-Tobin approach to corner

solutions using recreation data. Similar to the Kuhn-Tucker approach, the Amemiya-

Tobin approach begins with the maximization of a utility function. Corner solutions are

dealt with, however, in a two-stage process. In the first stage, desired consumption shares

are realized from the utility maximization process, while in the second stage consumption

shares falling below a certain level are truncated to zero, allowing the possibility of zero

consumption of a subset of the available goods. The model is estimated for a sample of

anglers visiting three New York sites, and the results are used to assess the probabilities of

visiting various combinations of sites as well as the sensitivity of desired shares to price

and catch rate variables.

Although they do not estimate a model, Bockstael, Hanemann, and Strand

(BHS,1986) were the first authors to discuss the Kuhn-Tucker model within the context

of recreation demand. They note that the presence of binding non-negativity constraints in

the maximization problem does not allow solutions for continuous demand equations to

exist. This in turn prevents solving for a continuous indirect utility function, which plays a

central role in welfare analysis in recreation demand models. BHS demonstrate, however,

that a discontinuous indirect utility function exists which can be used for welfare analysis.

To see this intuitively, the authors suggest examining the recreation decisions as consisting

of two choice components. For a recreation season, individuals must choose which subset

of sites to visit, and how many trips to make to each of the sites selected. Conditional on

the choice of which subset of sites to visit (the demand regime from the terminology

above), a conditional demand system solution can be can be solved from the Kuhn-Tucker

conditions, from which a conditional indirect utility function can be stated. There exists a conditional indirect utility function for each possible demand regime. The (unconditional) indirect utility function for use in welfare analysis is the maximum of the set of conditional indirect utility functions. Given this line of reasoning, consumers chose the demand regime which provides the highest level of utility, and allocate trips to the selected sites based on the conditional demand system for that regime. Derivation of the indirect utility function in the Kuhn-Tucker model will be formally presented in the following chapter.

A class of models closely related to the Kuhn-Tucker model are the discrete/continuous choice models of consumer demand. For completeness, they are briefly mentioned here. In these models, it is assumed that individuals face a decision of which of several mutually exclusive substitute goods to purchase, and how many units of the chosen good to consume. These models can be thought of as "extreme corner solution" models because it is assumed *a priori* that only one of the available substitutes will be consumed. Hanemann (1984b) develops a utility consistent estimation process and suggests empirical specifications for such models. Chiang and Lee (1992) further develop the econometrics of continuous/discrete choice models, allowing for the possibility that none of the available substitute goods are consumed. The restrictive assumption that only one of the substitute goods is consumed has limited the usefulness of continuous/discrete choice models in recreation demand, and applications have focused on situations where the restriction that only one good is consumed arises naturally. Examples include Chiang (1991), who applies the model to purchases of various brands of coffee, and Hewitt and Hanemann and (1995), who apply the model to residential demand for water. A

particularly interesting example of the continuous/discrete choice model is Ransom (1987a,b). In studying the labor supply of married men, household utility is assumed to depend on three goods: husband leisure time, wife leisure time, and money income, where leisure is defined to be time not spent working. The model is an extreme corner solution model because only one choice variable, the wife's work time, has a binding non-negativity constraint, implying there are two possible regimes: households in which the wife works, and households in which the wife does not work. Using a quadratic utility function specification, estimates of wage and income elasticities for married men are presented conditional on the work status of the wife.

2.4 The Dual Model

A dual approach to modeling corner solutions, beginning with the statement of an indirect utility function, was first suggested by Lee and Pitt (1986a) as a theoretically equivalent alternative to the Kuhn-Tucker estimation approach. Using their notation, the development of the model proceeds as follows. Let the indirect utility function be defined as

$$H(v;\theta,\varepsilon) = \max_{q}\{U(q;\theta,\varepsilon)|vq = 1\}, \qquad (2.21)$$

where $U(\cdot)$ is a strictly quasi-concave utility function, $\mathbf{q} = (q_1,...,q_M)'$ is a vector representing the goods being analyzed, $\mathbf{v} = (v_1,...,v_M)'$ is a vector of commodity prices normalized by income, θ is a vector of utility function parameters, and $\varepsilon = (\varepsilon_1,...,\varepsilon_M)'$ is a vector of stochastic error terms. Application of Roy's Identity allows the recovery of *notional demands*

$$q_i = \frac{\partial H(v;\theta,\varepsilon)}{\partial v_i} \bigg/ \sum_{j=1}^{M} v_j \frac{\partial H(v;\theta,\varepsilon)}{\partial v_j}, \quad i = 1,...,M. \tag{2.22}$$

The q_i's are considered notional because they may take negative values, since the original problem in (2.21) is stated without non-negativity constraints. Thus q is meaningless economically; its elements should be interpreted rather as latent variables corresponding to the observed demand vector $x = (x_1,...,x_M)'$ via the concept of virtual price. A virtual price is a type of reservation price that will exactly support zero consumption of a good. If the demands for the first k goods are observed to be zero, a vector of virtual prices $\pi = (\pi_1,...,\pi_k)'$ exactly supporting zero consumption can be solved using Roy's Identity from equation (2.22). Setting the equations for the non-consumed goods equal to zero yields

$$0 = \frac{\partial H(\pi_1(\bar{v}),...,\pi_k(\bar{v}),\bar{v},\theta,\varepsilon)}{\partial v_i}, \quad i = 1,...,k, \tag{2.23}$$

where $\bar{v}$ is the vector of prices for the positively consumed goods. Replacing the market prices with the virtual prices for the non-consumed goods in the remaining equations in (2.22) and setting them equal to the observed consumption level yields equations for the M-k positively consumed goods

$$x_i = \frac{\partial H(\pi_1(\bar{v}),...,\pi_k(\bar{v}),\bar{v},\theta,\varepsilon)}{\partial v_i} \bigg/ \sum_{j=1}^{M} v_j \frac{\partial H(\pi_1(\bar{v}),...,\pi_k(\bar{v}),\bar{v},\theta,\varepsilon)}{\partial v_j}, \tag{2.24}$$
$$i = k+1,...,M.$$

Note that only the market prices of the consumed goods are present in (2.24). Selection of the subset of goods to be consumed, known as the demand regime, is determined by

comparison of the virtual and actual prices. If the market price is higher than the virtual price, the good will not be consumed. The regime for which the first k goods are not consumed is characterized by

$$\pi_i(\bar{v}) \leq v_i, \quad i = 1, \ldots, k. \tag{2.25}$$

Equations (2.24) and (2.25) are used to state the probability of a particular consumption pattern, from which a likelihood function can be derived and the parameters of the indirect utility function recovered. This will be shown explicitly in the empirical specification outlined in the following chapter.

An intuitive explanation of the use of virtual prices in a two good model is provided in Figure 2.1. The utility maximizing observed consumption bundle in this case is a corner solution, where $x_1 = 0$ at market prices (p_1, p_2). If the utility function were maximized without regard for non-negativity constraints, the solution would be the notional demands (q_1, q_2), where the first good is consumed at a negative quantity. The virtual price π_1 for the first good is a reservation price at which consumption of the good is induced to be exactly zero. Note that in the case of a corner solution the market price is greater than the virtual price of the non-consumed good, whereas for an interior solution the market price would be less than the virtual price. Comparison of the virtual price with the market price can therefore be used to identify corner solutions.

The dual approach has seen only limited application due to the complexity of the model. Lee and Pitt (1987) apply a version of it to the production literature, estimating a translog cost function for three classes of energy inputs for firms in Indonesia. Own and
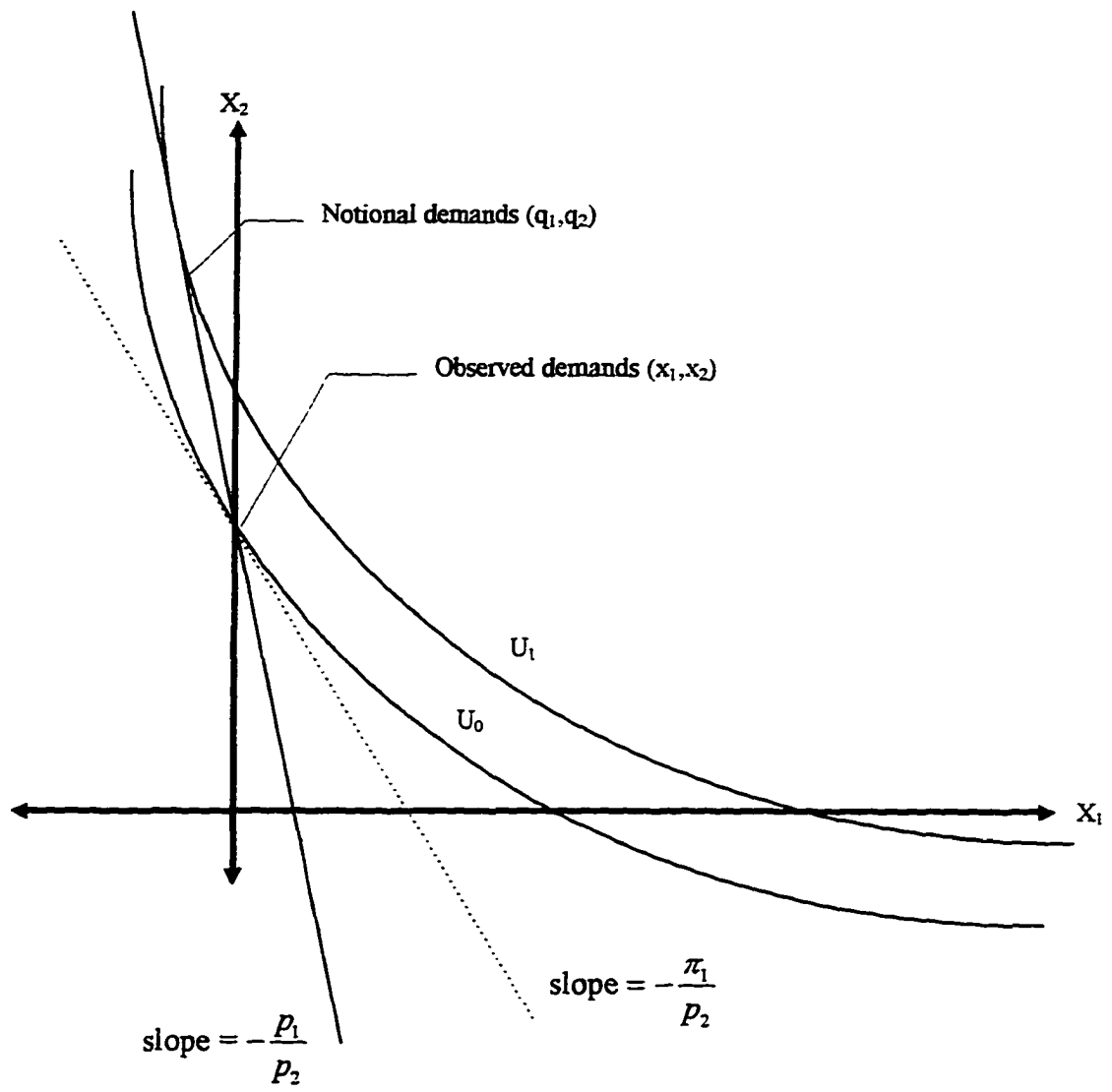
Figure 2.1 Example of Corner Solution and Virtual Price

cross price elasticities for the energy input demands are estimated conditional on the production regime to which the firm belongs. In a working paper, Lee and Pitt (1986b) estimate the demand for food items in Indonesia, reporting price elasticities. Srinivasan and Winer (1994) apply the dual model to estimate preferences for three brands of ketchup, which they use to form a market map for designing marketing strategy.

It is interesting to note that the dual method is theoretically equivalent to the Kuhn-Tucker method. Recalling the Kuhn-Tucker conditions from equation (2.16), the first order conditions for the first k of M available goods not consumed can be stated as

$$
\begin{aligned}
U_j - \lambda p_j &\leq 0, \quad j = 1, \ldots, k \\
U_j - \lambda p_j &= 0, \quad j = k+1, \ldots, M.
\end{aligned}
\tag{2.26}
$$

Given the assumptions on the structure of the utility function there exists a vector $\eta = (\eta_1, \ldots, \eta_M)'$ such that

$$
\eta_j = \frac{1}{\lambda} U_j, \quad j = 1, \ldots, M.
\tag{2.27}
$$

Equation (2.26) can then be rewritten

$$
\begin{aligned}
\eta_j &\leq p_j, \quad j = 1, \ldots, k \\
\eta_j &= p_j, \quad j = k+1, \ldots, M,
\end{aligned}
\tag{2.26'}
$$

and η can be interpreted as a vector of virtual prices. Thus equation (2.26') is equivalent to the regime determining conditions in equation (2.25). The dual and Kuhn-Tucker approaches are therefore theoretically equivalent, differing empirically in the approach to estimation of the underlying preferences.

There are several advantages to using the K-T or dual approach to estimate preferences for visits to recreation sites. Most importantly, both approaches are utility-theoretic, beginning with the maximization of a single utility function. The behavioral and econometric models are integrated so that the same error structure and explanatory variables are used to explain both the continuous and discrete aspects of the recreation decision, providing both theoretical and econometric advantages. Using the methods presented in the following chapter, it is possible to derive welfare measures for changes in site attributes which are derived from a theoretically solid characterization of the demand for the resource. Additionally, the dual approach provides a framework for using a flexible form indirect utility function, which can theoretically provide a second order approximation to any specification. In spite of these advantages there have been very few applications of either method. The likelihood functions for estimation are highly non-linear, and difficulties with estimation increase exponentially with increases in the number of goods being analyzed. To date only applications of the extreme corner solution model and applications examining three highly aggregated choice variables exist in the literature, with results focusing on presenting regime-specific marginal effects and elasticities rather than policy-relevant results. The Monte Carlo methods developed in this work for conducting welfare analysis in the context of the Kuhn-Tucker and dual models are computationally intense, requiring the use of long-running computer programs. Nonetheless, improved simulation and econometric methods for evaluating complicated likelihood functions, coupled with the availability of ever faster computers, should reduce the extent of the disadvantages associated with the use of these utility-consistent

approaches, making the Kuhn-Tucker and dual models operational at a time when household level data, and the prevalence of corner solutions associated with it, is becoming more and more available.

CHAPTER 3: DERIVATION OF ECONOMETRIC MODELS

The econometric models for the Kuhn-Tucker and dual approaches are explained
in the following sections. For each approach the empirical specification, derivation of the
estimating equations and the likelihood function, and theory for welfare analysis are
presented.

3.1 The Kuhn-Tucker Model

3.1.1 Empirical Specification

As noted above the Kuhn-Tucker model begins with the assumption that consumer
preferences over a set of M recreation goods and a numeraire good can be represented
using a random utility function, which they maximize subject to a budget constraint and a
set of non-negativity constraints. For the empirical application, the specification
suggested by Bockstael, Hanemann, and Strand (1986) is employed. In particular, it is
assumed that the consumer's direct utility function is a variant of the linear expenditure
system, with

$$U(\mathbf{x},z;\mathbf{q},\gamma,\varepsilon) = \sum_{j=1}^{M} \Psi_j(q_j,\varepsilon_j)\ln(x_j + \theta) + \ln(z) \tag{3.1}$$

and

$$\Psi_j = \exp\left(\sum_{s=1}^{S} \delta_s q_{js} + \varepsilon_j\right), \quad j = 1,...,M, \tag{3.2}$$

where $\gamma = (\delta,\theta)$ and q_{js} denotes the sth quality attribute associated with commodity j.

The Ψ_j's can be thought of as quality indices associated with each of the recreation sites.

An advantage of this specification is that the implicit equations for the ε_j's in

equation (2.18) resulting from the Kuhn-Tucker conditions can be explicitly solved, yielding the following first order conditions:

$$\varepsilon_j \leq g_j(\mathbf{x}, y, \mathbf{p}; \mathbf{q}, \gamma), \ x_j \geq 0, \ x_j g_j(\mathbf{x}, y, \mathbf{p}; \mathbf{q}, \gamma) = 0, \tag{3.3}$$

where

$$g_j(\mathbf{x}, y, \mathbf{p}; \mathbf{q}, \gamma) = \ln\left[\frac{p_j(x_j + \theta)}{y - \sum_{i=1}^{M} p_i x_i}\right] - \sum_{s=1}^{S} \delta_s q_{js}, \quad j = 1, \ldots, M. \tag{3.4}$$

As was noted in the previous chapter, for utility maximization problems with binding non-negativity constraints, only demand systems conditional on the demand regime can be recovered. For the case when the first k goods are consumed, the conditional demand equations have the form

$$x_j = \frac{1}{p_j}\left(\frac{\Psi_j(\cdot)}{1 + \sum_{l=1}^{K} \Psi_l(\cdot)}\right)\left(y - \theta\sum_{l=1}^{K} p_l\right) + \theta, \quad j = 1, \ldots, k, \tag{3.5}$$

which can be used to construct conditional indirect utility functions.

The linear expenditure system utility function is often considered a restrictive functional form, since it imposes the condition that all the goods being modeled are substitutes. Although certainly more general forms for the utility function exist, in the current application, where the intent is to model the substitutability between available recreation sites, this may not be an unreasonable restriction. In fact the specification is general enough to provide an opportunity to test for *weak complementarity* of preferences (Maler, 1974), which is often assumed *a priori* in recreation demand models. Imposing

weak complementarity implies there is only "use-value" associated with the commodities. In the absence of weak complementarity individuals may also assign "non-use" value to the commodity, implying the consumer receives utility from the availability of the good without actually consuming it.[1] The utility function in equation (3.1) exhibits weak complementarity only when $\theta = 1$. If $\theta \neq 1$, the quality index $\Psi_j(\cdot)$ enters the utility function for all the available sites, regardless of whether the sites are visited or not. Therefore the individual receives utility from the quality attributes of sites not visited, as well as those visited, implying the existence of non-use values.[2] Further discussion of weak complementarity and non-use value will be provided in the results chapter.

3.1.2 Derivation of Estimating Equations and Likelihood Function

For estimation it is necessary to specify a distribution for the random disturbance vector. For the current application it is assumed that the ε_i's are independent and identically distributed negative extreme value with parameters $\eta = 0$ and λ. The probability density function for the negative extreme value variate is (Bain and Englhart, 1992)

$$f_\varepsilon(-\varepsilon) = \frac{1}{\lambda} \exp\left\{[(-\varepsilon - \eta) / \lambda] - \exp[(-\varepsilon - \eta) / \lambda]\right\}, \tag{3.6}$$

---

[1] Formally weak complementarity can be defined as $x_i = 0 \Rightarrow \dfrac{\partial U(\cdot)}{\partial q_i} = 0$, i.e. the marginal utility of changes in a site's quality variable is zero if the good is not consumed.

[2] Freeman (1993) divides the value of environmental goods into use value, non-use value, and existence value. It is worth noting that revealed behavior models as considered here cannot elicit information on existence values.

where $\mu_\varepsilon = \eta - \lambda(0.5772)$ and $\sigma_\varepsilon^2 = \dfrac{\pi^2 \lambda^2}{6}$. An important feature of this specification is

that it provides closed form equations for the probabilities in equation (2.20), which are

used to construct the likelihood function. In particular, the probability of observing the

first k goods positively consumed is given by

$$\exp\left(-\sum_{j=1}^{K} \frac{g_j}{\lambda}\right) abs|J_k| \exp\left[-\sum_{j=1}^{M} \exp\left(\frac{-g_j}{\lambda}\right)\right], \tag{3.7}$$

where J_k denotes the Jacobian of the transformation from ε to $(x_1,\ldots,x_K,\varepsilon_{K+1},\ldots,\varepsilon_M)'$.

Allowing for the possibility that none of the goods of interest are consumed, there are 2^M

possible forms of the probability in (3.7) and 2^{M-1} possible non-trivial Jacobian

transformations. The Jacobian terms are messy algebraically and increase in difficulty with

the addition of goods being analyzed. For a four good model, the transformation terms

are given by

$$J_\omega = F_j \text{ for } \omega = \{1\}, \{2\}, \{3\}, \{4\} \tag{3.8a}$$

$$J_\omega = \prod_{j \in \omega} F_j - \prod_{j \in \omega} z_j \text{ for } \omega = \{1,2\}, \{1,3\}, \{1,4\}, \{2,3\}, \{2,4\}, \{3,4\} \tag{3.8b}$$

$$J_\omega = \prod_{j \in \omega} F_j - 2\prod_{j \in \omega} z_j - \sum_{j \in \omega} F_j \left(\prod_{\substack{k \in \omega \\ k \neq j}} z_k\right) \text{ for } \omega = \{1,2,3\}, \{1,2,4\}, \{1,3,4\}, \{2,3,4\} \tag{3.8c}$$

$$J_\omega = F_1 F_2 F_3 F_4 - 3z_1 z_2 z_3 z_4 + 2(F_1 z_2 z_3 z_4 + F_2 z_1 z_3 z_4 + F_3 z_1 z_2 z_4 + F_4 z_1 z_2 z_3) \tag{3.8d}$$
$$- (F_1 F_2 z_3 z_4 + F_1 F_3 z_2 z_4 + F_1 F_4 z_2 z_3 + F_2 F_3 z_1 z_4 + F_2 F_4 z_1 z_3 + F_3 F_4 z_1 z_2), \omega = \{1,2,3,4\},$$

where

$$z_j = \frac{p_j}{y - \sum_{k=1}^{4} p_k x_k} = \frac{\partial \varepsilon_k}{\partial x_j} \quad \forall k \neq j, \tag{3.9}$$

$$F_j = \frac{1}{x_j + \theta} + z_j = \frac{\partial \varepsilon_j}{\partial x_j} \quad \forall j, \tag{3.10}$$

and ω is the set of positively consumed goods.

3.1.3 Conditional Indirect Utility and Welfare Analysis

The primary purpose for estimating the structure of consumer preferences over a set of recreation goods is to provide a basis for welfare analysis. In particular, policy makers may be interested in the welfare implications of changing the price or quality characteristics of a set of recreation alternatives, or of reducing the number of alternatives available. Freeman (1993) reviews several types of welfare measures available to analysts, including compensating variation, which will be of concern here. Compensating variation is typically defined in the consumer choice literature in terms of the expenditure function. If $e(\mathbf{p}, y, \mathbf{q}, \gamma, u)$ is an expenditure function, where u is utility level, the compensating variation (C) associated with a change in price from $\mathbf{p}^0$ to $\mathbf{p}^1$ is

$$C = e(\mathbf{p}^1, y, \mathbf{q}, \gamma, u^0) - e(\mathbf{p}^0, y, \mathbf{q}, \gamma, u^0), \tag{3.11}$$

the difference between the expenditures required to sustain utility at the original level u^0 when price moves from $\mathbf{p}^0$ to $\mathbf{p}^1$. This definition provides the basis for the familiar expression of compensating variation as the area under the Hicksian demand curve. That is,

$$C = \int_{\mathbf{p}^0}^{\mathbf{p}^1} \frac{\partial e(\mathbf{p}, y; \mathbf{q}, \gamma, u^0)}{\partial \mathbf{p}} d\mathbf{p}. \tag{3.12}$$

An equivalent definition that is convenient for use in recreation demand models relies upon the indirect utility function. Formally let $V(\mathbf{p}, y; \mathbf{q}, \gamma, \varepsilon)$ denote the solution to a utility maximization problem similar to that in equation (3.1). The compensating variation associated with a change in the price and attribute vectors from $(\mathbf{p}^0, \mathbf{q}^0)$ to $(\mathbf{p}^1, \mathbf{q}^1)$ is implicitly defined by

$$V(\mathbf{p}^0, y; \mathbf{q}^0, \gamma, \varepsilon) = V(\mathbf{p}^1, y + C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma, \varepsilon); \mathbf{q}^1, \gamma, \varepsilon). \tag{3.13}$$

There are several attributes of the compensating variation measure that are worthy of note. First, from the analyst's perspective, $C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma, \varepsilon)$ is a random variable. Policy makers will typically be interested in the average value of this measure in the population, $\overline{C}(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma)$.[3] Second, the non-linearity of the utility maximization problem will typically preclude a closed form solution for C or its average. As a result, numerical techniques will be required to calculate it.

As noted in the previous chapter, the process of computing the indirect utility function and welfare measure within the context of the Kuhn-Tucker model can be clarified by considering the utility maximization as a two-stage process. The individual first maximizes his or her utility conditional on a set of binding non-negativity constraints and then chooses among the resulting conditional indirect utility functions. Formally, let

---

[3] Hanemann (1984a) discusses various statistics that can be reported to represent the central tendency of compensating variation in the population, in light of the fact that the welfare measure is a random variable. Bockstael and Strand (1987) point out that the interpretation of the source of the error term in

$$A = \left\{ \varnothing, \{1\}, \ldots, \{M\}, \{1,2\}, \{1,3\}, \ldots, \{1,2,\ldots,M\} \right\} \tag{3.14}$$

denote the collection of all possible subsets of the index set $I = \{1, \ldots, M\}$. A conditional

indirect utility function $V_\omega(\mathbf{p}_\omega, y; \mathbf{q}, \gamma, \varepsilon)$ can be defined for each $\omega \in A$ as the maximum

utility level the consumer can achieve when they are restricted to the commodities indexed

by ω. Formally:

$$V_\omega(\mathbf{p}_\omega, y; \mathbf{q}, \gamma, \varepsilon) = \underset{x,z}{Max}\, U(\mathbf{x}, z, \mathbf{q}, \gamma, \varepsilon) \tag{3.15}$$

s.t.

$$\sum_{j \in \omega} p_j x_j + z \leq y \tag{3.16a}$$

and

$$z \geq 0, x_j = 0, j \notin \omega, x_j \geq 0, j \in \omega, \tag{3.16b}$$

where $U(\mathbf{x}, z, \mathbf{q}, \gamma, \varepsilon)$ is the utility function defined in equation (3.1) and $\mathbf{p}_\omega = \{p_j : j \in \omega\}$

is the vector of commodity prices that have not been constrained to zero. Let

$\mathbf{x}_\omega = (\mathbf{p}_\omega, y; \mathbf{q}, \gamma, \varepsilon)$ denote the conditional demand levels (equation (3.5) above) solving

this utility maximization problem. Notice that, since the prices associated with those

commodities that have been forced to zero do not enter the budget constraint in (3.16a),

V_ω and $\mathbf{x}_\omega$ are functions of $\mathbf{p}_\omega$ and not $\mathbf{p}$. However, since the direct utility function does

not *a priori* exhibit weak complementarity, the conditional indirect utility function will

depend on the entire vector of quality attributes $\mathbf{q}$, and not simply $\mathbf{q}_\omega = \{q_j : j \in \omega\}$.

---

the model has implications for computation of the welfare effect in the population. For the analysis that
follows, the assumption that the errors result from unobserved components of preferences is maintained.

Constraining a subset of the commodities to have zero consumption provides no assurance that the optimal consumption levels for the remaining commodities will be positive. Let

$$\tilde{A} = \tilde{A}(\mathbf{p}, y; \mathbf{q}, \gamma, \varepsilon) = \left\{ \omega \in A : x_{\omega j}(\mathbf{p}_\omega, y; \mathbf{q}, \gamma, \varepsilon) > 0, \forall j \in \omega \right\} \tag{3.17}$$

denote the collection of ω's for which the corresponding conditional utility maximization problem yields an interior solution. The original consumer maximization problem can then be viewed as a two-stage problem in which the conditional indirect utility functions are computed for each $\omega \in A$ and then the consumer chooses the V_ω from the set of feasible indirect utility functions that maximizes his or her utility. That is

$$V(\mathbf{p}, y; \mathbf{q}, \gamma, \varepsilon) = \underset{\omega \in \tilde{A}}{Max} \left\{ V_\omega(\mathbf{p}_\omega, y; \mathbf{q}, \gamma, \varepsilon) \right\}. \tag{3.18}$$

The computation of the compensating variation in equation (3.13) then corresponds to implicitly solving for $C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma, \varepsilon)$ in

$$\begin{aligned}
&\underset{\omega \in \tilde{A}^0}{Max} \left\{ V_\omega(\mathbf{p}_\omega^0, y; \mathbf{q}^0, \gamma, \varepsilon) \right\} = \\
&\underset{\omega \in \tilde{A}^1}{Max} \left\{ V_\omega(\mathbf{p}_\omega^1, y + C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, \gamma, \varepsilon); \mathbf{q}^1, \gamma, \varepsilon) \right\}.
\end{aligned} \tag{3.19}$$

Note that the index collection $\tilde{A}$ may change as a result of the changing price and/or quality attribute level, or through the elimination of an alternative from the available set.

There are three difficulties associated with computing $\overline{C}(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma)$ in practice. First, for a given ε and γ, $C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma, \varepsilon)$ is an implicit function for which no closed form exists. A numerical procedure such as numerical bisection must be employed. Second, given $C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma, \varepsilon)$ and γ, $\overline{C}(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma)$ does not

have a closed form solution, requiring the use of Monte Carlo integration. Errors can be

drawn from the estimated underlying distribution for ε, $f_\varepsilon(\varepsilon)$, and the average of the

resulting $C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma, \varepsilon)'s$ forms an estimate of $\overline{C}$.[4] Third, given an algorithm for

computing $\overline{C}(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma)$, the analyst does not typically have available γ, but

rather an estimator $\hat{\gamma} \sim g_{\hat{\gamma}}$. Thus any computation of $\overline{C}$ will itself be a random variable,

dependent upon the distribution of the estimated parameters. The procedure developed by

Krinksy and Robb (1986) can be employed to approximate the statistical properties of $\hat{C}$,

the estimate of $\overline{C}$, by repeatedly drawing realizations from $g_{\hat{\gamma}}$ and computing $\hat{C}$ for each

of these realizations. The above elements are combined into the following numerical

algorithm:

- A total of N_γ parameter vectors (i.e., $\gamma^{(i)}, i = 1, ..., N_\gamma$) are randomly drawn from the distribution $g_{\hat{\gamma}}$.

- For each $\gamma^{(i)}$ and each observation in the sample $(n = 1, ..., N)$ a total of N_ε vectors of random disturbances terms (i.e., $\varepsilon^{(ink)}, k = 1, ..., N_\varepsilon$) are drawn from the estimated distribution for ε, $f_\varepsilon(\varepsilon)$.

- Substituting $\gamma^{(i)}$ and $\varepsilon^{(ink)}$ for γ and ε in equation (3.19), numerical bisection can be used to solve for C, with the result labeled $C^{(ink)}$.

- Averaging the $C^{(ink)}$'s over the N_ε disturbance vectors and N observations in the sample yields a point estimate $\hat{C}^{(i)}$, a Monte Carlo integration evaluation of $E_\varepsilon\left[C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y, \gamma^{(i)}, \varepsilon)\right]$.

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[4] Geweke (1996) provides a useful review of Monte Carlo integration.

- The distribution of the $\hat{C}^{(i)}$'s provides the basis for characterizing the distribution of the mean compensating variation of interest in light of the uncertainty regarding γ. The mean value of $\hat{C}^{(i)}$ over the N_γ parameter draws provides a consistent estimate of $\overline{C}$. The distribution of the $\hat{C}^{(i)}$'s can be used to construct standard errors for the estimate of $\overline{C}$.

3.2 The Dual Model

3.2.1. Empirical Specification

In a manner similar to the Kuhn-Tucker model, we begin by assuming preferences for trips to M recreation sites can be represented using duality theory by a random indirect utility function. Furthermore, it is assumed that the indirect utility function is weakly separable in the recreation goods. This implies a two-stage budgeting process, where in the first stage the individual chooses expenditure on recreation and all other goods, and in the second stage the recreation expenditures are allocated among the available sites. The indirect utility function under this assumption is specified as a function of a subutility function for recreation goods, taking the form $V(\mathbf{p}, y) = V(V_r(\mathbf{p}_r, y_r), \mathbf{p}_a, y_a)$ where $V_r(\cdot)$ is the recreation subutility function, $\mathbf{p}_r$ and y_r are prices and expenditures for recreation goods, and $\mathbf{p}_a$ and y_a are prices and expenditures for all other goods. We will be concerned with analyzing the second step of the two-stage budgeting process, treating recreation expenditures as predetermined. The assumption of weak separability is common in applied demand studies, although not without its drawbacks. Edgerton (1997) discusses weak separability in the general context of demand estimation, while LaFrance (1993) provides a careful overview of weak separability and its ramifications for applied welfare analysis, concluding that the assumption will tend to bias the welfare measure.

The Kuhn-Tucker model presented above does not treat recreation spending as predetermined. The ramifications of this for the comparability of the two models will be addressed in the chapter describing the estimation results.

Following Lee and Pitt (1986) and Srinivasan and Winer (1994), the recreation subutility function is represented using the flexible form translog indirect utility function. That is,

$$\ln V(\mathbf{p}(y), \gamma, \varepsilon) = \alpha_0 + \sum_{i=1}^{M} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=i}^{M} \sum_{j=1}^{M} \beta_{ij} \ln p_i \ln p_j + \sum_{i=1}^{M} \varepsilon_i \ln p_i, \qquad (3.20)$$

where $V(\cdot)$ is indirect subutility, $\mathbf{p} = (p_1, ..., p_M)'$ is a vector of prices normalized by total recreation expenditures y, $\varepsilon = (\varepsilon_1, ..., \varepsilon_M)'$ is a vector of error terms, and $\gamma = (\alpha, \mathbf{B})$ are parameters of the utility function, where $\alpha = (\alpha_0, ..., \alpha_M)'$, $\mathbf{B} = (\beta_1, ..., \beta_M)'$, and $\beta_j = (\beta_{j1}, ..., \beta_{jM})$. As is standard practice with the use of the translog function (Christensen, et al., 1975), we assume equality and symmetry restrictions on the $\mathbf{B}$ matrix. That is,

$$\sum_{i=1}^{M} \beta_{ij} = \sum_{i=1}^{M} \beta_{ik}, \quad j, k = 1, ..., M, \qquad (3.21a)$$

$$\beta_{ij} = \beta_{ji}, \quad i, j: i \neq j. \qquad (3.21b)$$

For model tractability it is necessary to assume additional structure on the utility function. The equality assumption is strengthened to

$$\sum_{i=1}^{M} \beta_{ij} = \sum_{j=1}^{M} \beta_{ij} = 0, \qquad (3.22)$$

and the error terms are restricted such that

$$\sum_{i=1}^{M} \varepsilon_i = 0. \tag{3.23}$$

It is necessary for welfare analysis purposes to include variables describing the characteristics of the recreation sites in the model. Within the context of the translog function it is convenient to define the α_i's as functions of site quality variables. If a linear relationship is assumed

$$\alpha_i = -\sum_d \delta_d q_{id}, \quad i = 1, \ldots, M, \tag{3.24}$$

where $\mathbf{q}_i = (q_{i1}, \ldots, q_{id})'$ is a vector of quality variables for the ith site and the δ_d's are parameters. It is required that the α_i's are defined such that

$$\alpha_i < 0, \quad i = 1, \ldots, M. \tag{3.25}$$

This restriction is necessary for an unambiguous interpretation of the β_{ij} parameters in the notional share equations

$$p_i q_i = \left(\alpha_i + \sum_{j=1}^{M} \beta_{ij} \ln p_j + \varepsilon_i\right) \Big/ \sum_{l=1}^{M} \alpha_l, \quad i = 1, \ldots, M, \tag{3.26}$$

which are recovered via application of the logarithmic form of Roy's identity to (3.20) and enforcement of the restrictions in (3.21), (3.22), and (3.23). Note that with the restriction in equation (3.25), $\alpha_i \Big/ \sum_{l=1}^{M} \alpha_l$ enters the share equations positively, and $\beta_{ij} \Big/ \sum_{l=1}^{M} \alpha_l$ is the own or cross price effect of the jth price on the ith good.

---

[5] Applications employing the translog function typically use the restriction $\sum_{i-1}^{M} \alpha_i = -1$. In the current study this was not desirable, since each α_i is constructed from site-specific variables.

3.2.2. Derivation of Estimating Equations

As described in the previous chapter, the estimation process proceeds using virtual prices. Assuming the first k sites are not visited, the logs of the virtual prices for these sites are obtained by setting the notional stochastic share equations in (3.26) to zero for $i = 1, \ldots, k$ and solving simultaneously, yielding

$$
\begin{bmatrix} \ln \pi_1 \\ \cdot \\ \cdot \\ \cdot \\ \ln \pi_k \end{bmatrix} = -\mathbf{B}_k^{-1} \begin{bmatrix} \alpha_1 + \sum_{j=k+1}^{M} \beta_{1j} \ln p_j \\ \cdot \\ \cdot \\ \alpha_k + \sum_{j=k+1}^{M} \beta_{kj} \ln p_j \end{bmatrix} - \mathbf{B}_k^{-1} \begin{bmatrix} \varepsilon_1 \\ \cdot \\ \cdot \\ \cdot \\ \varepsilon_k \end{bmatrix}, \tag{3.27}
$$

where

$$
\mathbf{B}_k = \begin{bmatrix} \beta_{11} & \cdot & \cdot & \beta_{1k} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ \beta_{k1} & \cdot & \cdot & \beta_{kk} \end{bmatrix}.
$$

For the first k goods not to be consumed their market prices must exceed their virtual prices. This is equivalent to

$$
\begin{bmatrix} \varepsilon_1 \\ \cdot \\ \cdot \\ \cdot \\ \varepsilon_k \end{bmatrix} \geq \begin{bmatrix} t_1 \\ \cdot \\ \cdot \\ \cdot \\ t_k \end{bmatrix}, \tag{3.28}
$$

where

$$
\begin{bmatrix} t_1 \\ \cdot \\ \cdot \\ \cdot \\ t_k \end{bmatrix} = - \begin{bmatrix} \alpha_1 + \sum_{j=k+1}^{M} \beta_{1j} \ln p_j \\ \cdot \\ \cdot \\ \cdot \\ \alpha_k + \sum_{j=k+1}^{M} \beta_{kj} \ln p_j \end{bmatrix} - \mathbf{B}_k \begin{bmatrix} \ln p_1 \\ \cdot \\ \cdot \\ \cdot \\ \ln p_k \end{bmatrix}.
$$

For the remaining positively consumed M-k goods the virtual prices from (3.27) are substituted into the remaining Roy's identity equations in (3.26) and set equal to the observed expenditure shares such that

$$
s_i = \left[\alpha_i + \sum_{j=1}^{K} \beta_{ij} \ln \bar{\pi}_j + \sum_{j=k+1}^{M} \beta_{ij} \ln p_j + \varepsilon_i + \eta_i \right] \Big/ A, \quad i = k+1,\dots,M-1, \quad (3.29)
$$

where

$$
\eta_i = (\mathbf{B}_k^i)(\mathbf{B}_k^{-1}) \begin{bmatrix} \varepsilon_1 \\ \cdot \\ \cdot \\ \cdot \\ \varepsilon_k \end{bmatrix},
$$

$$
A = \sum_{i=1}^{M} \alpha_i ,
$$

$$
\mathbf{B}_k^i = (\beta_{i1},\dots,\beta_{ik}) ,
$$

s_i is the observed expenditure share for the ith good, $\ln \bar{\pi}$ is the deterministic component of the virtual price in (3.27), and $i = k+1,\dots,M-1$ because the Mth share is not independent. Rearranging (3.29) gives

$$
\varepsilon_i = t_i, \quad i = k+1,\dots,M-1, \tag{3.30}
$$

where

$$t_i = s_i A - \left[\alpha_i + \sum_{j=1}^{k} \beta_{ij} \ln \overline{\pi}_j + \sum_{j=k+1}^{M} \beta_{ij} \ln p_j + \eta_i \right].$$

Equations (3.28) and (3.30), along with the specification of the joint density function $f_\varepsilon(\varepsilon)$ for ε, provide the necessary information to construct the likelihood function for estimation. The contribution to the likelihood function for an individual who visits M-k of the available sites is

$$\int_{t_1}^{\infty} \cdots \int_{t_k}^{\infty} g(\varepsilon_1, \ldots, \varepsilon_k) h(\varepsilon_{k+1} = t_{k+1}, \ldots, \varepsilon_{M-1} = t_{M-1} | \varepsilon_1, \ldots, \varepsilon_k) \left| A^{M-k-1} \right| d\varepsilon_1 \ldots d\varepsilon_k \quad (3.31)$$

where $g(\cdot)$ is a marginal distribution and $h(\cdot)$ is a conditional distribution. The $\left| A^{M-k-1} \right|$ term is the relatively simple Jacobian transformation from ε to $(\varepsilon_1, \ldots, \varepsilon_k, s_{k+1}, \ldots, s_{M-1})'$. There are 2^{M-1} possible consumption regimes for which a probability such as (3.31) can be constructed, from which the likelihood function is formed as the product of the appropriate probabilities and maximum likelihood used to recover estimates of the indirect subutility function parameters.

Lee and Pitt (1987) and Srinivasan (1989) describe in detail an additional estimation issue pertaining to the dual approach. The econometric model specified above provides no guarantee that the model is coherent, i.e. that the probabilities for the different demand regimes sum to one. Within the context of the translog indirect utility function Van Soest and Kooreman (1990) propose that the following conditions are sufficient to ensure model coherency:

- B positive semi-definite

- $1 - \sum_{i=1}^{M} \sum_{j=1}^{M} \beta_{ij} \ln p_j > 0$

- $Be \geq 0$, $e = (1,\ldots,1)'$.

The last two conditions are met by the parameter restrictions already imposed on the model. There is no guarantee, however, that the first condition will be met. Previous applications of the dual approach have imposed the restriction that all the diagonal elements of B be positive (implying negative own price effects), and the off-diagonal elements negative (implying positive cross price effects) to ensure model coherency. In travel cost models, where prices are based on travel distance to the site, this may be too restrictive. We may expect cross price effects for sites which are geographically close (and hence whose prices are closely correlated) to have negative cross price effects, even though the goods may be viewed as substitutes. Additional restrictions are therefore not placed on the B matrix; the estimated parameters are rather tested to determine if they meet the coherency condition. This topic will be further discussed in the results presented in Chapter 5.

3.2.3 Derivation of Likelihood Function for a Four Good Model

For estimation it is assumed that $\varepsilon \sim N(0, \sigma^2 \Sigma)$, where $\Sigma = \{r_{ij}\}$ and r_{ij} denotes the correlation between ε_i and ε_j. Since it is assumed that the error terms add up to zero, the correlation between any M-1 of the errors can be specified with the constraint

$$\sum_{\substack{j=1 \\ i<j}}^{M-1} r_{ij} = \frac{2-M}{2},$$

(3.32)

where the left hand side is the sum of correlations between all pairs of any M-1 of the errors. This implies there are $[(M-1)(M-2)/2]-1$ free parameters in Σ, in addition to the variance σ^2 (Srinivasan, 1989). The previous applications of the dual approach have examined problems with three choice-variables, for which there are no free parameters in Σ. In a four-good model, there are two free parameters in Σ and the error variance which must be estimated. In the application that follows a four site model of recreation demand is examined. Attempts to estimate a simulated four-good model with two free correlation terms, however, were unsuccessful. For the remainder of the analysis the exchangeability assumption is therefore adopted. Under exchangeability (see Gelman, et al. (1995) or Durrett (1996) for a complete description), it is assumed that the joint distribution of $\varepsilon = (\varepsilon_1, ..., \varepsilon_M)'$ is invariant to permutations of the indexes $(1, ..., M)$. This assumption implies Σ has the structure

$$\Sigma = \begin{bmatrix} 1 & r & r & r \\ r & 1 & r & r \\ r & r & 1 & r \\ r & r & r & 1 \end{bmatrix},$$

(3.33)

i.e. $r_{ij} = r \ \forall \ i \neq j$. Furthermore, given that the errors sum to zero, it can be shown from equation (3.32) that $r = -1/3$ for a four-good model. The correlation matrix of interest for the remaining analysis therefore becomes

$$\Sigma = \begin{bmatrix} 1 & -1/3 & -1/3 & -1/3 \\ -1/3 & 1 & -1/3 & -1/3 \\ -1/3 & -1/3 & 1 & -1/3 \\ -1/3 & -1/3 & -1/3 & 1 \end{bmatrix}. \tag{3.33'}$$

Assuming that the errors are normal is convenient in that the likelihood function in equation (3.31) contains the product of a marginal and conditional distribution, which are then themselves normal probability density functions. Yong (1990) provides derivations of the conditional mean and variance terms which, along with the specification for Σ in equation (3.33), are used to derive the likelihood function. In a four good model, there are four types of demand regimes to consider:

Type 1: All goods are consumed.

This is the interior solution. The likelihood contains three of the goods, since the fourth is not independent. The likelihood function is

$$\phi(\varepsilon_1 = t_1, \varepsilon_2 = t_2, \varepsilon_3 = t_3)|A^3|, \tag{3.34}$$

where the t_i's are computed from equation (3.30) and $\phi(\cdot)$ is the normal probability density function with mean zero and variance matrix given by

$$\Sigma_{123} = \sigma^2 \begin{bmatrix} 1 & -1/3 & -1/3 \\ -1/3 & 1 & -1/3 \\ -1/3 & -1/3 & 1 \end{bmatrix}. \tag{3.35}$$

Type 2: Three goods (say 1, 2 and 3) consumed and one not consumed (say 4).

Only goods 1 and 2 enter the function, since good 3 is not independent. The likelihood function is

$$\int_{t_4}^{\infty} \phi_c(\varepsilon_1 = t_1, \varepsilon_2 = t_2)\phi_m(\varepsilon_4)|A^2|d\varepsilon_4, \tag{3.36}$$

where the t_i's are computed as in equations (3.28) and(3.30), $\phi_c(\cdot)$ is the normal

probability density function with mean

$$\mu_{12|4} = (-\frac{\varepsilon_4}{3}, -\frac{\varepsilon_4}{3}) \tag{3.37}$$

and variance

$$\Sigma_{12|4} = \sigma^2 \begin{bmatrix} 8/9 & -4/9 \\ -4/9 & 8/9 \end{bmatrix}, \tag{3.38}$$

and $\phi_m(\cdot)$ is the univariate normal density function with mean zero and variance σ^2.

Type 3: Two goods consumed (say 1 and 2) and two not consumed (say 3 and 4).

The function contains only goods 1, 3, and 4 since the share for good 2 is not

independent. The likelihood function is

$$\int_{t_4}^{\infty}\int_{t_3}^{\infty} \phi_c(\varepsilon_1 = t_1)\phi_m(\varepsilon_3, \varepsilon_4)|A|d\varepsilon_3 d\varepsilon_4 \tag{3.39}$$

where the t_i's are computed as in equations (3.28) and(3.30), $\phi_c(\cdot)$ is the univariate

normal density with mean $\mu_{1|34} = -\frac{\varepsilon_3}{2} - \frac{\varepsilon_4}{2}$ and variance $\Sigma_{1|34} = \frac{2}{3}\sigma^2$, and $\phi_m(\cdot)$ is the

bivariate normal density with mean zero and variance

$$\Sigma_{34} = \sigma^2 \begin{bmatrix} 1 & -1/3 \\ -1/3 & 1 \end{bmatrix}. \tag{3.40}$$

Type 4: One good (say good 4) consumed and three goods not (say 1, 2, and 3).

The likelihood function in this case is

$$\int_{t_3}^{\infty}\int_{t_2}^{\infty}\int_{t_1}^{\infty} \phi(\varepsilon_1,\varepsilon_2,\varepsilon_3)\,d\varepsilon_1 d\varepsilon_2 d\varepsilon_3, \tag{3.41}$$

where the t_i's are computed as in equation (3.28) and $\phi(\cdot)$ is the normal density with mean zero and variance as in equation (3.35).

3.2.4 Welfare Analysis

As was the case with the Kuhn-Tucker model, the primary reason for estimating preferences using the dual model is to provide an internally consistent, utility theoretic platform to conduct welfare analysis. We will again be interested in obtaining an estimate of the compensating variation in the population for changes in site attributes or availability. Many of the same issues discussed above apply to the dual model as well. Once again compensating variation (C) is the amount of money necessary to restore the individual to their original utility level following a change in price or quality, implicitly defined in the equation

$$V(\mathbf{p}^0,y,\mathbf{q}^0,\gamma,\varepsilon)=V(\mathbf{p}^1,y+C(\mathbf{p}^0,\mathbf{q}^0,\mathbf{p}^1,\mathbf{q}^1,y,\gamma,\varepsilon);\mathbf{q}^1,\gamma,\varepsilon). \tag{3.42}$$

Numerical methods will again be employed to estimate $\overline{C}$ in the population.

As in the Kuhn-Tucker model, the indirect utility function of interest for welfare analysis will be discontinuous. Recall that the indirect subutility function in (3.20) is computed without non-negativity constraints, allowing the possibility of negatives shares. Economically meaningful shares are obtained using virtual prices, from which conditional indirect utility functions can be constructed for each possible demand regime. The indirect

utility function of interest for welfare analysis is the maximum of the set of conditional indirect utility functions. Following similar logic as above, let

$$D = \left\{ \{1\}, \dots, \{N\}, \{1,2\}, \{1,3\}, \dots, \{1,2,\dots,M\} \right\} \tag{3.43}$$

denote the collection of all possible non-empty subsets of the index set $I = \left\{1, \dots, M\right\}$, each representing a possible demand regime. Note that since in the dual model weak separability has been assumed, implying that for all individuals in the sample at least one of the analyzed goods is consumed, the null set is not included in equation (3.43) as it was in equation (3.14). Rewriting the subutility function in equation (3.20) as $V(\mathbf{p}, y, \mathbf{q}, \gamma, \varepsilon)$ to make explicit in the function the presence of recreation expenditure y and quality attributes $\mathbf{q}$, a conditional indirect utility function can be defined for each $\omega \in D$ as

$$V_\omega(\mathbf{p}_\omega, y, \mathbf{q}, \gamma, \varepsilon) = V(\mathbf{p}_\omega, \pi(\mathbf{p}_w), y, \mathbf{q}, \gamma, \varepsilon), \tag{3.44}$$

where the commodities indexed by ω are consumed, $\mathbf{p}_\omega = \left\{ p_j : j \in \omega \right\}$, and $\pi(\mathbf{p}_\omega)$ is the vector of virtual prices for the non-consumed goods. Application of the logarithmic form of Roy's identity to $V_\omega(\mathbf{p}_\omega, y, \mathbf{q}, \gamma, \varepsilon)$ yields conditional share equations $\mathbf{s}_\omega(\mathbf{p}_\omega, y, \mathbf{q}, \gamma, \varepsilon)$, the utility maximizing consumption levels conditional on the given regime. Note that both V_ω and $\mathbf{s}_\omega$ are functions of $\mathbf{q}$ and not $\mathbf{q}_\omega = \{q_j : j \in \omega\}$, since the indirect utility function in equation (3.20) does not exhibit the property of weak complementarity.

Constraining a subset of the commodities to zero via virtual prices provides no assurance that the shares for the remaining goods will be positive. Let

$$\widetilde{D} = \left\{ \omega \in D : s_{\omega j}(\mathbf{p}_\omega, y, \mathbf{q}, \gamma, \varepsilon) > 0 \ \forall j \in D \right\} \tag{3.45}$$

denote the set of ω's for which the corresponding conditional indirect utility function

yields non-negative shares. The non-notional indirect utility function of interest for

welfare analysis is then the maximum of the feasible conditional indirect utility functions.

That is

$$V(\mathbf{p}, y, \mathbf{q}, \gamma, \varepsilon) = \underset{\omega \in \tilde{D}}{Max} \{V_\omega(\mathbf{p}_\omega, y, \mathbf{q}, \gamma, \varepsilon)\}. \tag{3.46}$$

The computation of compensating variation in equation (3.42) corresponds to

implicitly solving for $C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, y; \gamma, \varepsilon)$ in

$$
\begin{aligned}
\underset{\omega \in \tilde{D}^1}{Max} \{V_\omega(\mathbf{p}_\omega^0, y, \mathbf{q}^0, \gamma, \varepsilon)\} = \\
\underset{\omega \in \tilde{D}^2}{Max} \{V_\omega(\mathbf{p}_\omega^1, y + C(\mathbf{p}^0, \mathbf{q}^0, \mathbf{p}^1, \mathbf{q}^1, \gamma, \varepsilon), \mathbf{q}^1, \gamma, \varepsilon)\}.
\end{aligned}
\tag{3.47}
$$

The practical difficulties associated with solving for $\overline{C}$ in equation (3.47) are

identical to those outlined above for the Kuhn-Tucker model. The same numerical

algorithm can be applied to arrive at an estimate of the central tendency in the population

in the context of the dual model. Details of the use of the numerical algorithm in both the

Kuhn-Tucker model and the dual model are presented in Chapter 5.

CHAPTER 4: DATA

The Kuhn-Tucker and dual models are applied to data on Wisconsin Great Lakes sports angling. The data are drawn primarily from two mail surveys conducted in 1990 at the University of Wisconsin-Madison by Richard Bishop and Audrey Lyke. The surveys solicited information on angling behavior during the 1989 season from Wisconsin Great Lakes trout and salmon anglers and non-Great Lakes Wisconsin anglers. The sample was drawn from Wisconsin fishing license sales records to avoid the bias associated with on-site sampling and to include the effects of non-users of the Great Lakes in analyzing use of the resource. Of the 3384 license holders that were drawn, 64% responded to a screening postcard. Of these, 368 anglers indicated they had fished the Great Lakes for trout or salmon in 1989 and were mailed a Great Lakes angler survey; 270 useable surveys were returned. 1385 anglers reported fishing in Wisconsin in 1989, but did not visit the Great Lakes. 301 of these individuals were sent an inland angler survey, of which 239 were returned in useable form. In total 509 observations are available for this study. Closer inspection of the data showed that 4 of the individuals who filled out Great Lakes surveys did not visit the Great Lakes; thus for this study there are 266 Great Lakes angler observations and 243 non-Great Lakes angler observations. Further details concerning sampling procedures and survey design, as well as copies of both the Great Lakes and inland survey, are available in Lyke (1993). A rich amount of information concerning both Great Lakes and non-Great Lakes anglers is provided by the survey results. Variables are available describing numbers of trips taken over the entire season to Wisconsin Great Lakes fishing areas, travel costs associated with visiting each site, the type of angling

preferred (charter fishing, private boat fishing, pier fishing, etc.), and variables reflecting attitudes toward characteristics of the lakes.

4.1 Trip Variables

Data are available on the number of trips taken during the 1989 season to 22 distinct Great Lakes fishing destinations. For modeling purposes these destinations have been combined into four aggregate "sites":

- South Lake Michigan

- North Lake Michigan

- Green Bay

- Lake Superior.

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 are considered by the recreationist. A model which is highly disaggregated will potentially include non-relevant sites, understating the probability of selecting relevant sites. Highly aggregated models reduce this type of bias but cannot distinguish between decisions to visit unique destinations within an aggregated site. The main concern arising from these aggregation issues is that benefit estimates tend to be sensative to aggregation decisions. Although Parsons and Kealy (1992) have demonstrated a method for avoiding aggregation in RUM models by randomly drawing each individual's opportunity 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 high degree of aggregation in this study is less an issue than in those cited above, since the variation in the physical charateristics of the destinations in each site is small compared to the large geographical differences in the four sites. The aggregation of the 22 destinations into the four sites is summarized in Table 4.1. The numbers in parentheses correspond to the numbers on the map of Wisconsin in Figure 4.1, which shows the geographical locations of the destinations and aggregate sites.

Table 4.2 characterizes the distribution of site usage found in the survey data. It is interesting to note that while many of the users of the Great Lakes (72%) visit only one site during the season, a substantial percentage (28%) visit more than one site, yet less than 2% visit all the available sites. This distribution is typical of multiple site recreation demand data sets, emphasizing the need for models that address the presence of general corner solutions. Summary statistics for the trip variables are presented in Table 4.3.

4.2 Price Variables

In travel cost models, the price of the recreation good is the cost of getting to the site, and any on-site expenditures. It is necessary to compute the price for all sites for all individuals, regardless if they visited the site or not. The cost of getting to the site typically has two components: the direct travel costs and the opportunity cost of travel time. The surveys provide information on the distance in miles from each respondent's home to each of the 22 destinations and the type of vehicle typically driven. Round trip

Table 4.1 Aggregation of Destinations into Sites

South Lake Michigan	North Lake Michigan	Green Bay	Lake Superior
Kenosha (1)	Manitowoc (6)	Door County-W (12)	Saxon Harbor (16)
Racine (2)	Two Rivers (7)	Green Bay (13)	Ashland (17)
Milwaukee (3)	Kewaunee (8)	Oconto (14)	Washburn (18)
Port Washington (4)	Algoma (9)	Marinette (15)	Bayfield (19)
Sheboygan (5)	Sturgeon Bay (10)		Cornucopia (20)
	Door County-E (11)		Port Wing (21)
			Superior (22)

Table 4.2 Distribution of Site Usage in Survey Data

Sites Visited	Number of Observations
All four sites, $\omega=\{1,2,3,4\}$	3
South and North Lake Michigan and Green Bay, $\omega=\{1,2,3\}$	13
South and North Lake Michigan and Lake Superior, $\omega=\{1,2,4\}$	1
South Lake Michigan, Green Bay, and Lake Superior, $\omega=\{1,3,4\}$	0
North Lake Michigan Green Bay, and Lake Superior, $\omega=\{2,3,4\}$	7
South and North Lake Michigan, $\omega=\{1,2\}$	13
South Lake Michigan and Green Bay, $\omega=\{1,3\}$	4
South Lake Michigan and Lake Superior, $\omega=\{1,4\}$	8
North Lake Michigan and Green Bay, $\omega=\{2,3\}$	19
North Lake Michigan and Lake Superior, $\omega=\{2,4\}$	10
Green Bay and Lake Superior, $\omega=\{3,4\}$	2
South Lake Michigan, $\omega=\{1\}$	85
North Lake Michigan, $\omega=\{2\}$	46
Green Bay, $\omega=\{3\}$	11
Lake Superior, $\omega=\{4\}$	49
No sites visited, $\omega=\varnothing$	243

Wisconsin
Lake Superior

Lake Superior

19
20
18
22   21
17
16

Michigan (upper peninsula)

Wisconsin

Green Bay

15
12   11
14
10
9
13   8
7
North
Lake Michigan
6

5

South
Lake Michigan
4

3

2
1   *Lake*
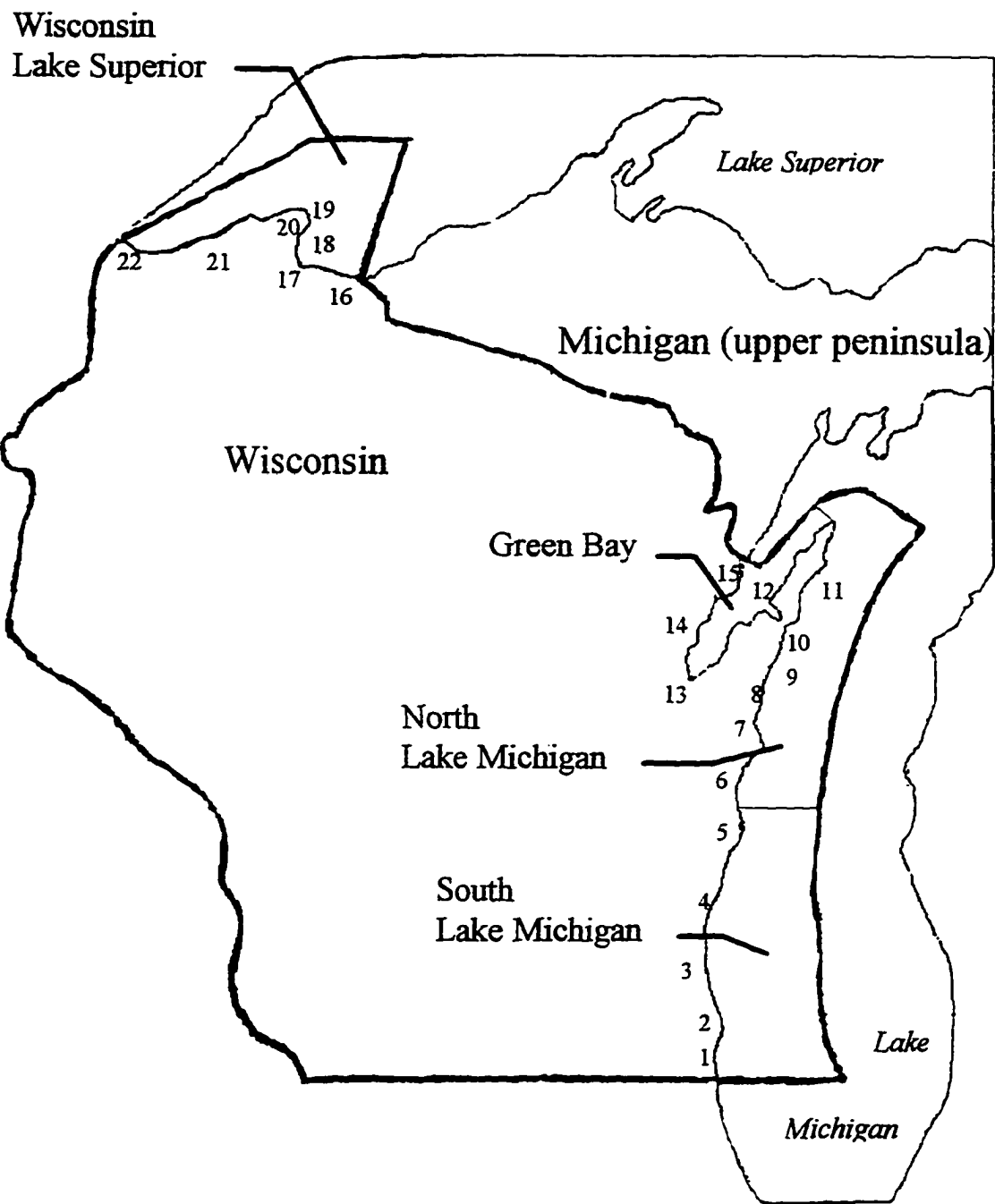
Michigan

Figure 4.1 Wisconsin Great Lakes Destinations and Sites

Table 4.3 Summary Statistics for Trip and Price Variables

	South Lake Michigan	North Lake Michigan	Green Bay	Lake Superior
full sample				
1989 Fishing	2.35	1.56	0.65	2.75
Trips	(8.92)	(6.32)	(3.07)	(13.33)
Price	85.88	123.70	129.11	177.84
	(139.62)	(172.92)	(173.54)	(172.59)
users only				
1989 Fishing	4.50	2.99	1.25	5.27
Trips	(11.96)	(8.51)	(4.17)	(19.09)
Price	93.04	123.97	128.65	163.83
	(101.75)	(112.41)	(109.65)	(123.36)

Notes: Mean income for sample is $43,585.

Mean income for users only is $45,563.

direct travel costs for each individual to each destination were computed by multiplying the total number of miles traveled for a given individual-destination combination by the cost per mile for the vehicle class driven, as provided by the American Automobile Association.

Computing the opportunity cost of time component of the price is less straight forward. There is a large literature dedicated to addressing the proper way to model time spent traveling to recreation sites and time spent visiting a site. The shadow value of time has been addressed by McConnell and Strand (1981), Smith, et al. (1983), Bockstael, Strand, and Hanemann (1987), and Larson (1993a). Accounting for time spent on-site, which brings econometric challenges in the form of endogenous prices if individuals can choose the duration of the visit, has been examined by Kealy and Bishop (1986), McConnell (1992), and Larson (1993b). Larson, Shaikh, and Loomis (1997) lay out a conceptual framework for integrating the labor-leisure choice in a household utility model with a recreation demand model. A natural extension of the models presented here is to combine the household labor-leisure decision, from which corner solutions often arise, with a corner solution model of recreation demand. Conceptually such a model would account for the shadow price of leisure time in the demand for recreation goods. For the present study a simple means of accounting for time costs is used. McConnell and Strand (1981) present results that suggest that in empirical models of recreation demand, one-third of the wage rate is a reasonable approximation to the hourly opportunity cost of time. The time cost component of price for each destination-individual combination is therefore computed as

$$\frac{1}{3}W(\text{round trip distance})\Big/45mph,$$

where the wage is calculated from annual income assuming 2000 work hours per year, and 45 miles per hour travel time is assumed.

The price of visiting a destination is the sum of the direct travel cost and opportunity cost of travel time. It is the price of visiting a site that enters the econometric models, however. This is computed as the most frequently visited destination within the site if the angler used the site, or the average of the individual's destination prices within the site if the site was not visited. Table 4.3 provides summary statistics for the price variables, as well as income.

4.3 Site Attribute Variables

One can imagine several attributes of recreation sites which would influence visitation decisions. Many of these may be intangible, such as general beauty and peacefulness, but several are quantifiable. For angling these are likely to include anticipated success of fishing, the quality and cleanliness of the water resource, and accessibility to the resource. Combinations of these are examined for the current study.

Catch rates are clearly important since the likelihood of angling success is often a major determinant of the recreation decision. Furthermore, state, federal, and local agencies currently spend large amounts of time and money to influence catch rates in the Great Lakes region through stocking programs and regulations. The inclusion of catch rates as a quality attribute in the model will allow them to be used to conduct welfare analyses of existing and/or alternative fishery management programs.

Catch rate data for the 1989 fishing season is available from the Wisconsin Department of Natural Resources for the major sport fishing species. Of particular interest are four aggressively managed salmonoid species: lake trout, rainbow (or steelhead) trout, Coho salmon, and Chinook salmon. Angling success rates for each of these species at each of the 22 disaggregate destinations used in the surveys are available. Furthermore, these catch rates are broken down by angling method (or mode), including private boat, charter fishing, and pier/shore angling. To take advantage of these mode-differentiated catch rates, data from the surveys were used to label respondents as private boat anglers, charter boat anglers, or shore anglers. Great Lakes anglers were asked to answer detailed questions on the two most frequently visited Great Lakes destinations, including the angling mode. Based on these answers, fishing modes are assigned to the Great Lakes anglers as follows:

- Individuals using the same mode at both destinations were assigned that mode.

- Individuals who fished from a private boat at one of the destinations, and indicated ownership of a boat, were labeled private boat anglers.

- Individuals who fished from a charter boat and a private boat and made less than ten trips during the season were considered charter boat anglers. If they made more than ten trips they were considered private boat anglers.

- Individuals who fished from a charter boat and from shore and made less than ten trips during the season were considered charter boat anglers. If they made more than ten trips they were considered shore anglers.

- Those not belonging to one of the descriptions above were considered shore anglers.

The anglers who did not visit the Great Lakes were considered private boat anglers if they indicated ownership of a boat suitable for the Great Lakes, and shore anglers if they did not. Of the 266 Great Lakes anglers, 82 were assigned the charter mode, 141 were assigned the private boat mode, and 43 were considered shore anglers. Of the 243 inland anglers, 24 were considered private boat anglers, and the remaining 219 where assigned the shore angler mode. Based on their angling mode, each individual angler is assigned a catch rate for each species at each of the 22 destinations. Catch rates for each species at each site are calculated as the catch rate from the most frequently visited destination in the site if the site is visited, or the average of the destinations in the site if it is not. Table 4.4 summarizes the catch rate variables. The users-only section of Table 4.4 also includes a catch rate index, defined as the sum of catch rates for the four species, since this will be used in the specification of the dual model.

The environmental quality of the water resource is also likely to affect recreation decisions. Varying degrees of contaminants are found in fish, water, sediments, and the atmosphere in the Great Lakes region. Toxin levels in fish are used in this study because they provide a good proxy for overall water quality, as they are correlated with many other types of pollution (De Vault, et al., 1996). In addition, toxin levels in fish are responsible for fish consumption advisories in the region. De Vault, et al. (1989) provide a study of toxin levels in lake trout flesh during the relevant time period, with samples taken from three locations in the Wisconsin Great Lakes region. The average toxin levels

Table 4.4 Site Quality Variables

	South Lake Michigan	North Lake Michigan	Green Bay	Lake Superior
full sample				
Lake Trout Catch Rate	.029	.022	.001	.046
	(.045)	(.030)	(.002)	(.059)
Chinook Salmon Catch Rate	.027	.048	.036	.010
	(.024)	(.030)	(.032)	(.014)
Coho Salmon Catch Rate	.040	.005	.005	.028
	(.053)	(.005)	(.008)	(.021)
Rainbow Trout Catch Rate	.012	.018	.001	.001
	(.013)	(.026)	(.002)	(.001)
Effective Toxin Level	3.464	2.270	2.270	.597
	(2.847)	(1.866)	(1.866)	(.491)
users only				
Lake Trout Catch Rate	.050	.038	.001	.082
	(.052)	(.032)	(.002)	(.059)
Chinook Salmon Catch Rate	.041	.065	.050	.018
	(.023)	(.031)	(.037)	(.014)
Coho Salmon Catch Rate	.068	.007	.007	.041
	(.058)	(.006)	(.010)	(.018)
Rainbow Trout Catch Rate	.017	.031	.002	.002
	(.014)	(.029)	(.002)	(.001)
Catch Rate Index	.179	.143	.061	.145
	(.133)	(.086)	(.051)	(.085)
Effective Toxin Level	3.48	2.28	2.28	.60
	(2.84)	(1.88)	(1.88)	(.49)

Note: Catch rates are reported as catch per person hour of effort.

(ng/kg-fish) from this study are used, matched on the basis of proximity to the four

aggregate sites, to form a basic toxin measure T_j $(j = 1,...,4)$ for each site.[1] However,

toxin levels are likely to influence visitation decisions only if the consumer perceives that

the toxins create a safety issue. The survey asked respondents if the toxin levels in fish

were of concern to them. This information is used to form an "effective toxin level"

variable $E_j = T_j D$, where $D=1$ indicates that the respondent was concerned about toxin

levels in fish and $D=0$ otherwise. The average effective toxin levels for each site are

presented in Table 4.4 above.

The accessibility of the resource also affects the recreation decision. The Great

Lakes are large bodies of water which require special equipment to fish effectively, and

ownership of a suitable boat is a major advantage in this type of fishery. Use of a dummy

variable B=1 to indicate boat ownership and B=0 otherwise is explored. Among all

respondents to the surveys, 24% indicated ownership of a boat. Among users of the Great

Lakes, 37% indicated boat ownership.

4.4 Quality Index Terms

There are many ways in which the site attribute variables can enter the econometric

model. Because estimation of the Kuhn-Tucker model places fewer demands on the data,

it is possible to construct the quality index terms in equation (3.2) using the individual

catch rates and toxin terms. In the results chapter to follow, the Kuhn-Tucker model with

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[1] While a variety of toxins are reported in the De Vault, et al (1989) study, the levels of toxins 2,3,7,8-TCDD are used, which are generally responsible for the fish consumption advisories in the Great Lakes region.

$$\Psi_j(\mathbf{q}_j, \varepsilon_j) = \exp[\delta_0 + \delta_{lk}R_{lk,j} + \delta_{ch}R_{ch,j} + \delta_{co}R_{ch,j} + \delta_{rb}R_{rb,j} + \delta_E E_j + \varepsilon_j],$$
$$j = 1,\dots,4,$$

(4.1)

will be considered the main empirical specification, where $R_{k,j}$ denotes the catch rate for

species k and site j, with $k=lk$ for lake trout, ch for Chinook salmon, co for Coho salmon,

and rb for rainbow trout. Alternative forms will also be explored, including the use of the

boat dummy variable and a catch rate index term.

The dual model, with its higher degree of difficulty in estimation and parameter

restrictions, does not allow as general of a specification. Recalling that the α_i's contain

the site characteristics in the translog function, equation (3.24) in the main dual model

specification is defined as

$$\alpha_i = \delta_0 B + \delta_1 CAT_i, \quad i = 1,\dots,4,$$

(4.2)

where CAT is a catch rate index defined as

$$CAT_i = R_{lk,j} + R_{ch,j} + R_{co,j} + R_{rb,j}, \quad i = 1,\dots,4.$$

(4.3)

The main model does not include the toxin variable, since preliminary estimations showed

problems with its use relating to the fact that it enters utility negatively, causing violations

of the restriction in equation (3.25) in some observations. The exclusion of the toxin

variable will be further discussed in the following chapter, along with potential variations

on the main dual model.

CHAPTER 5: ESTIMATION RESULTS

In the following sections, results from the estimation of the Kuhn-Tucker and dual models are presented. The empirical performance of the two models is discussed and the results are compared to estimates from a version of the linked model.

5.1 Kuhn-Tucker Model Estimation Results

5.1.1 Main Model Estimation

The main Kuhn-Tucker model presented in Chapter 3 was estimated for the 509 users and non-users of the Wisconsin Great Lakes, using the maximum likelihood procedure in the computer program TSP. The resulting parameter estimates are provided in Table 5.1. All of the parameters have the expected signs and, with the exception of the coefficient on lake trout catch rates, are statistically different from zero at a 5% critical level or less. For example, one would expect that higher toxin levels would reduce the perceived quality of a site, which is the case in the estimated model. On the other hand, higher catch rates should enhance site quality. This is the case for each of the four species considered. Furthermore, the small and statistically insignificant coefficient on lake trout is not unexpected, since among anglers lake trout are often considered a less desirable species. The other salmonoid species have a "trophy" status not shared by lake trout. In addition, the eating quality of lake trout is generally considered inferior to that of other species, particularly in the warmer waters of Lake Michigan.

The other coefficient of direct interest in Table 5.1 is θ. Recall from Chapter 3 that the parameter θ provides a means of testing for the presence of non-use value. The

Table 5.1 Estimated Parameters for Main Kuhn-Tucker Model

Parameter	Estimate	P-Value
δ_0 (Intercept)	-8.53	< .001
δ_{lt} (Lake Trout)	0.10	.953
δ_{ch} (Chinook Salmon)	13.39	< .001
δ_{co} (Coho Salmon)	3.12	.023
δ_{rb} (Rainbow Trout)	8.61	.035
δ_E (Effective Toxin Level)	-0.06	.018
θ	1.76	< .001
λ	1.29	< .001
$\theta-1$	0.76	< .001

assumption of weak complementarity, which is used extensively in recreation demand, holds only if $\theta = 1$. The results in Table 5.1 indicate this restriction is not borne out for this specification. In particular, θ is statistically different from "1" using a 1% critical level, suggesting that some non-use value is associated with the four Great Lakes angling sites. The fact that θ is significantly different from "1" but not largely different in magnitude has intuitive appeal in that one would expect the largest component of Freeman's (1993) value definitions to be use value for a fisheries resource. This is as opposed to a resource such as a wilderness preserve, where one might expect larger non-use and existence values. This is further pursued in the welfare section below.

5.1.2 Variations on the Main Model

For purposes of comparison with the dual model estimates presented below and to determine the robustness of the model to specification and error assumptions it was desirable to estimate variations on the main model. Three variations are presented here:

- Variation A: Inclusion of boat dummy variable

- Variation B: Use of catch rate index term and boat dummy variable

- Variation C: Assumption of normal errors.

The results of estimation are presented in Tables 5.2, 5.3, and 5.4, respectively.

In variations A and B, estimation of the variance term λ and weak complementary term θ are quite robust to the variable specification changes. In each case θ is significantly different from "1", implying that weak complementarity is still rejected. The coefficient on toxins is also stable over the two new specifications. The coefficients on catch rates in

Table 5.2 Kuhn-Tucker Variation A: Inclusion of Boat Dummy Variable

Parameter	Estimate	P-Value
δ_0 (Intercept)	-9.08	< .001
δ_{lk} (Lake Trout)	-0.87	.62
δ_{ch} (Chinook Salmon)	12.47	< .001
δ_{co} (Coho Salmon)	5.18	<.001
δ_{rb} (Rainbow Trout)	15.33	<.001
δ_E (Effective Toxin Level)	-0.06	<.001
δ_B (Boat Dummy Variable)	1.21	<.001
θ	1.64	< .001
λ	1.32	< .001

Table 5.3 Kuhn-Tucker Variation B: Use of Catch Rate Index and Boat Variable

Parameter	Estimate	P-Value
δ_0 (Intercept)	-9.99	< .001
δ_c (Catch Rate Index)	4.95	<.001
δ_E (Effective Toxin Level)	-0.05	.032
δ_B (Boat Dummy Variable)	1.22	<.001
θ	1.57	< .001
λ	1.36	< .001

variation A can be directly compared to the main model and are of a similar order of magnitude, although the sign on the lake trout coefficient is now negative and insignificant. Some of the p-values in the new estimation are also lower. The coefficient on the boat dummy variable is positive and significant, indicating ownership of a boat improves the quality of fishing at each of the sites. In variation B, the boat coefficient estimate is robust to the use of the catch rate index in place of the individual species catch rates. Although the catch rate index coefficient is not directly comparable to the main model, it is interesting to note that the estimate is roughly an average of the species-specific coefficients in the main model.

Variation C involved a more challenging estimation process. It is now assumed that the errors are independent, identically distributed $N(0, \sigma^2)$. This assumption does not change the derivation of the estimating equations or the Jacobian transformation terms, but does of course change the structure of the likelihood function. The computer package GAUSS was used to estimate the same set of coefficients as in the main model, with the parameter λ being replaced by σ, the standard deviation of the normal errors. Estimation of the complete model, however, failed to converge, with the estimate of σ becoming large without bound.. Estimation was successful when a value for σ was assumed. Table 5.4 presents the results for $\sigma = 2$.[1] It is interesting to note that given this assumption, the parameter estimates are fairly robust between the two error assumptions.

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[1] This value was chosen because the resulting parameter estimates compare favorably with the main model. Larger values for σ provide a similar model fit but increased p-values. Smaller values resulted in non-intuitive signs on the estimated coefficients.

Table 5.4 Kuhn-Tucker Variation C: Assumption of Normal Errors $(\sigma = 2)$

Parameter	Estimate	P-Value
δ_0 (Intercept)	-8.08	< .001
δ_{lt} (Lake Trout)	0.95	.32
δ_{ch} (Chinook Salmon)	12.75	< .001
δ_{co} (Coho Salmon)	6.65	.001
δ_{rb} (Rainbow Trout)	7.36	.06
δ_E (Effective Toxin Level)	-0.06	.02
θ	1.97	< .001

Weak complementarity is still rejected, and the coefficient on lake trout is still

insignificant. Caution must be exercised when interpreting these results, however, since

$\sigma = 2$ need not be the value which maximizes the likelihood function. Further

investigation is needed to draw reliable conclusions from the assumption of normal errors.

5.1.3 Welfare Analysis

The estimated Kuhn-Tucker model provides the means for constructing welfare

estimates of changes in environmental quality or site availability that are computed in an

internally consistent and utility theoretic framework. In this subsection the main model in

Table 5.1 and variations on it, along with the numerical procedure developed in Chapter 3,

are used to evaluate a series of policy scenarios for the Wisconsin Great Lakes region.

The Great Lakes region provides many opportunities for policy-relevant welfare

experiments as the lakes are heavily managed. The fishery itself is, in many ways,

artificially created and maintained. Of the major species included in the model, only lake

trout are native to both Lake Superior and Lake Michigan. Rainbow trout were

introduced around the turn of the century, while the salmon species were not present until

the 1950's. These species now reproduce naturally in the lakes, but are heavily augmented

with stocking programs. The lakes have also been invaded by exotic species, including the

sea lamprey. A parasite accidentally introduced in the 1930's, the sea lamprey decimated

lake trout populations in the lakes. Efforts to reintroduce naturally reproducing lake trout

to Lake Superior have been successful, while in Lake Michigan a fishable population is

maintained completely through stocking. Expensive sea lamprey control efforts continue

to this day. Finally, there are ongoing efforts throughout the Great Lakes region to

maintain and improve the fisheries by monitoring and controlling the flow of pollutants from commercial and industrial sources. For each of these forms of intervention, the natural policy question arises as to whether the benefits of these programs are sufficient to offset the corresponding costs. The Kuhn-Tucker model can be used to assess program benefits. As an illustration of this capability, welfare effects are estimated for the following hypothetical policies:

- Scenario A: Loss of Lake Michigan Lake Trout. Under this first policy scenario, state and local efforts to artificially stock lake trout in Lake Michigan and Green Bay would be eliminated. It is assumed that this would drive lake trout catch rates to zero in Lake Michigan, since the species is only naturally reproducing in Lake Superior.

- Scenario B: 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. Again, it is assumed that the corresponding Coho catch rates would be driven to zero for the Lake Michigan sites.[2]

- Scenario C: Increase in Lake Michigan Rainbow Trout. State and local efforts to artificially stock rainbow trout in the Lake Michigan sites are increased, leading to a twenty percent increase in rainbow trout catch rates for each of the three sites.

- Scenario D: Reduced Toxin Levels. For this policy scenario, the welfare implications of a twenty percent reduction in toxin levels at all four sites are considered.

- Scenario E: Loss of South Lake Michigan Site. Under the final policy scenario, changes in environmental control laws in the large population centers surrounding southern Lake Michigan cause the site to no longer be suitable for recreation fishing.

For each of these scenarios, average compensating variation in the population of

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[2] Coho salmon do, in fact, naturally reproduce in Lake Michigan, so that the elimination of stocking programs would not drive the associated catch rates completely to zero. However, $R_{\infty,j} = 0$ is used to make comparisons to Scenario A more direct.

Wisconsin fishing license holders $\overline{C}$ was estimated using the following procedure:

- A total of $N_\gamma = 250$ parameter vectors (i.e. $\gamma^{(i)}, i = 1,...,N_\gamma$) were randomly drawn from the asymptotically justified normal distribution for the maximum likelihood parameter estimates $\hat{\gamma}$ in Table 5.1.

- For each $\gamma^{(i)}$ and each observation in the sample ($n = 1,...,509$) a total of $N_\varepsilon = 1000$ vectors of random disturbances terms (i.e., $\varepsilon^{(ink)}, k = 1,..., N_\varepsilon$) were drawn from the estimated distribution for ε.

- Substituting $\gamma^{(i)}$ and $\varepsilon^{(ink)}$ for γ and ε in equation (3.19), numerical bisection was used to solve for C, with the result labeled $C^{(ink)}$.

- Averaging the $C^{(ink)}$'s over the N_ε disturbance vectors and N observations in the sample yields an estimate $\hat{C}^{(i)}$ for average compensating variation for the jth draw from the estimated parameter distribution.

The distribution of the $\hat{C}^{(i)}$'s provides the basis for characterizing the distribution of the

mean compensating variation of interest in light of the uncertainty in the parameter

estimates in Table 5.1. The mean of the $\hat{C}^{(i)}$'s over the parameter draws provides a

consistent estimate of $\overline{C}$. The welfare estimates and corresponding standard deviations

are reported for the five scenarios in Table 5.5.

The total compensating variations in Table 5.5 have the expected signs and relative

magnitudes, given the parameter estimates in Table 5.1. As expected, the loss of Coho

salmon in Lake Michigan (Scenario B) has a greater impact on consumer welfare than the

lost of lake trout (Scenario A). In particular, anglers would need to be compensated an

average of almost $275 per season for the loss of the Coho salmon population, as opposed

to less than $40 for the loss of lake trout. Furthermore, the lake trout benefits are not

Table 5.5 Welfare Estimates from Main Kuhn-Tucker Model
(Standard Deviations in Parentheses)

Policy Scenario	Mean Compensating Variation	
	Total	Use Only
Scenario A: Loss of Lake Trout in Lake Michigan	39.78 (143.05)	28.28 (97.56)
Scenario B: Loss of Coho Salmon in Lake Michigan	274.18 (123.18)	186.51 (80.79)
Scenario C: A 20% Increase in Lake Michigan Rainbow Trout	-77.67 (37.01)	-50.39 (22.54)
Scenario D: A 20% Reduction in Toxins in all Sites	-74.76 (26.13)	-50.31 (17.07)
Scenario E: Loss of South Lake Michigan Site	719.48 (114.20)	614.22 (90.59)

significantly different from zero using any reasonable confidence interval, whereas the

Coho benefits are significant at a 5% critical level. The lake trout results are particularly

interesting from a policy perspective, since so much effort has gone into rehabilitating the

lake trout fishery during the past three decades.[3]

In Scenario C it is shown that anglers would be willing to pay on average

approximately $78 for a 20% increase in the rainbow trout catch rates in Lake Michigan,

while Scenario D shows that decreasing pollution levels in the lakes would have a

substantial impact on angler welfare. Anglers would be willing to pay on average almost

$75 for a 20% reduction in toxins levels. The welfare calculations in scenarios C and D

are significant at the 5% confidence level.

In the final scenario, it is shown that the loss of the entire South Lake Michigan

site would require an average compensation of $719.48 per angler per season. This large

and statistically significant estimate is not surprising in light of the fact that this relatively

extreme policy scenario eliminates the most heavily used of the Wisconsin Great Lakes

sites.

As was noted in the previous subsection, the Kuhn-Tucker model estimates reject

the often assumed notion of weak complementarity, implying the total compensating

variation estimates in Table 5.5 are comprised of both use and non-use components. Since

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[3] One must use caution in concluding from this figure that the effort that has gone into rehabilitating the lake trout has not been worthwhile. There is an extensive debate on the proper way to manage the Great Lakes, with many believing that native species such as lake trout should be emphasized to maintain the lakes in their natural state. These values will not typically be represented in revealed preference studies, since they are more akin to existence value. This is an example of a situation where revealed preference and stated preference models can be viewed as complimentary rather than competing, with each measuring a unique component of total value.

policy makers are typically most interested in the use value associated with this type of resource, an interesting question is what portion of the estimates are due purely to use values.

To answer this question the non-use component is first isolated by setting the prices of the sites at or above their choke prices, so that use is choked off at the relevant sites.[4] The procedure outlined above for computing $\overline{C}$ is then followed, with the resulting welfare measure being entirely associated with non-use of the resource. Use value estimates are obtained by subtracting these non-use values from the total values reported in column two of Table 5.5. The use values are presented in column three of Table 5.5. As expected, the use value of the resource represents the majority of the total value in all cases.

Point estimates of the welfare effects resulting from variations A and B on the main model are presented in Tables 5.6 and 5.7 respectively. These estimates are computed using the estimated model parameters and the last three steps from the numerical procedure above. Confidence intervals are not computed for the estimates due to the amount of computer time that would be required. The point estimates are therefore conditional on the estimated parameters.

Variation A results in welfare estimates that are on the same order of magnitude as the main model. Since the coefficient estimate on lake trout is negative, the resulting welfare measure has a negative sign, implying the loss of lake trout in Lake Michigan

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[4] The use and non-use components of the welfare estimates for scenario E are computed differently than those for scenarios A-D. A formal explanation of both processes is presented in the appendix.

Table 5.6 Welfare Estimates from Kuhn-Tucker Variation A

Policy Scenario	Mean Compensating Variation	
	Total	Use Only
Scenario A: Loss of Lake Trout in Lake Michigan	-78.13	-54.82
Scenario B: Loss of Coho Salmon in Lake Michigan	485.40	354.82
Scenario C: A 20% Increase in Lake Michigan Rainbow Trout	-129.12	-87.35
Scenario D: A 20% Reduction in Toxins in all Sites	-68.09	-46.83
Scenario E: Loss of South Lake Michigan Site	907.40	800.57

Table 5.7 Welfare Estimates from Kuhn-Tucker Variation B

Policy Scenario	Mean Compensating Variation	
	Total	Use Only
Scenario A: Loss of Lake Trout in Lake Michigan	503.62	372.31
Scenario B: Loss of Coho Salmon in Lake Michigan	461.06	340.41
Scenario C: A 20% Increase in Lake Michigan Rainbow Trout	-47.93	-34.50
Scenario D: A 20% Reduction in Toxins in all Sites	-60.97	-43.11
Scenario E: Loss of South Lake Michigan Site	946.38	853.84

provides a utility increase. It is likely, however, that the welfare estimate is not significantly different from zero, given that the parameter estimate is not statistically significant. Scenarios B and C produce welfare measures which are larger than in the main model. Although the difference between the rainbow welfare effects in the two models is quite large, the estimate for the Coho effect falls within a 90% confidence interval generated by the main model. The estimate of the toxin effect for variation A is essentially the same as in the main model, while the site loss estimate, although larger in the variation, is on the same order of magnitude. As in the main model, the use value components of compensating variation represent the majority of the total value.

Variation B provides welfare estimates using the catch rate index as opposed to the individual species. For scenarios D and E, which do not involve changing catch rates, the results are fairly robust to the main model, with the estimate of the toxin effect being statistically identical and the site loss effect being larger but of a reasonable magnitude. The differences come in the estimates involving changes to catch rates, particularly in the lake trout scenario. Variation B results in an estimate of approximately $500 per angler for the loss of lake trout in Lake Michigan, as opposed to an insignificant loss in the main model. This is driven by the fact that use of the catch rate index does not allow the model to reflect differences in angler preferences for the various species. All species are equally valued by the coefficient on the index, resulting in welfare estimates differentiated by the magnitudes of the individual catch rates. This result seems to imply the use of a catch rate index is improper when there may be differences in angler preferences for different species, while it may be a reasonable simplification if there are not large differences in

preferences. Survey questions can be designed to ascertain this information, aiding in the model specification decision.

Welfare estimates for variation C were computed, but are not reported due to the fact that the parameter estimates are based on only a partial estimation. Nonetheless the welfare estimates were fairly robust to those from the main model, providing a preliminary indication of the robustness of the model to the error distribution assumption.

5.2 Dual Model Estimation Results

5.2.1 Main Model Estimation

The main dual model was estimated under the separability assumption described in Section 3.2 for the 266 Great Lakes anglers in the Wisconsin data using the maximum likelihood routine in the computer program GAUSS. As noted in Chapter 3, the assumption of exchangeability is maintained, implying the correlation between all pairs of the errors is equal to negative one third.

The estimation results for the main model given the error structure assumption are presented in Table 5.8. The estimates of the coefficients on the boat indicator variable and catch rate index are significant and of the expected sign, meeting the restriction condition from equation (3.25) and implying that boat ownership and catch rates affect utility positively. The restrictions in equations (3.21) and (3.22) imply there are six free parameters in the matrix B. Estimates of the off-diagonal elements of B are presented, while the remaining elements can be computed as functions of these. As discussed in Chapter 3, Van Soest and Kooreman (1990) note that a sufficient condition for model

Table 5.8 Main Dual Model Estimation Results

Parameter	Estimate	P-Value
δ_0 (Boat)	0.5187	<.001
δ_1 (Catch Rate Index)	4.0392	<.001
β_{12} (South Lake Michigan/ North Lake Michigan)	-0.1198	.1698
β_{13} (South Lake Michigan/ Green Bay)	-0.1611	.1957
β_{14} (South Lake Michigan/ Lake Superior)	-0.3316	.0400
β_{23} (North Lake Michigan/ Green Bay)	0.3173	.0155
β_{24} (North Lake Michigan/ Lake Superior)	-0.3716	.0344
β_{34} (Green Bay/Lake Superior)	-0.7978	.0042
σ (Standard Deviation of ε)	1.9249	<.001

coherency (the probabilities of each demand regime adding up to one) is that B be positive semi-definite, which the estimated parameters meet without the application of further restrictions.[5]

An estimate of the own and cross price effects on the notional shares is presented in Table 5.9.[6] Since these represent effects on notional expenditure shares, interpretation of the magnitude of these numbers is difficult. The signs of the estimated parameters do have intuitive appeal, however. All own price effects are negative as would be expected for non-Giffen goods. With one exception all cross price terms are positive, implying the goods are net substitutes. This is to be expected when modeling recreation goods which are closely related The cross price term between North Lake Michigan and Green Bay is positive, implying these two goods have a share complementary relationship. This means if the prices of all the other goods rise, the consumption share of visits to both North Lake Michigan and Green Bay will increase. Since prices of the goods are based on travel distance and Green Bay and North Lake Michigan are geographically close, this is an encouraging and intuitive result.

5.2.2 A Variation on the Main Model

Estimation of the dual model is much more challenging than the Kuhn-Tucker, and

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[5] A variety of starting values were used in numerous runs of the estimation program. As would be expected in a highly non-linear estimation process, the parameter estimates are somewhat sensitive to starting values. Nonetheless estimates resulting from other starting values were generally within a standard deviation of those reported, all estimation results were consistent with model coherency requirements, and the estimates of own and cross price effects on notional expenditure were robust to changes in the starting values.

[6] This was computed as $\hat{B} \Big/ sample\,mean(\sum_{i=1}^{N} \hat{\alpha}_i)$, where $\hat{\alpha}_i = \hat{\delta}_0 B + \hat{\delta}_1 CAT_i$.

Table 5.9 Estimates of Own and Cross Price Effects on Notional Shares

	South Lake Michigan	North Lake Michigan	Green Bay	Lake Superior
South Lake Michigan	-0.21	0.04	0.05	0.11
North Lake Michigan	0.04	-0.06	-0.11	0.13
Green Bay	0.05	-0.11	-0.22	0.27
Lake Superior	0.11	0.13	0.27	-0.51

hence more complicated specifications are difficult to estimate. Attempts were made to estimate models using individual catch rates, the toxin variable, and combinations of them. Use of the individual catch rates resulted in non-intuitive signs on the coefficient estimates and low p-values, due to the small number of observations available and the large demand the estimation of so many parameters places on the data. Most specifications including the toxin variable (or functions of it) either failed to converge or failed in attempts to calculate the variance of the estimated parameters. This is due to the fact that toxins enter the quality index with an opposite sign as the catch rates, causing violations of the restriction in equation (3.25) or driving the sum of the quality indices to zero for some of the observations.[7] Efforts to re-parameterize the model using the exponent of the quality index to allow the inclusion of the toxin variable also failed to provide satisfactory results.

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[7] Recall from equation (3.26) that the share equations are divided by the sum of the quality indices.

For completeness, a variation on the main model which includes the individual catch rates for lake trout and rainbow trout, and a salmon variable defined as the sum of the Coho salmon and Chinook salmon catch rates, is presented in Table 5.10. The estimates of own and cross price effects on notional expenditure shares from this specification are available in Table 5.11.

As expected, the estimation of more parameters placed additional demands on the data, and the coefficients are generally not as significant as in the main model. Nonetheless the signs and magnitudes of the estimates conform well to expectations. The estimates of the off-diagonal elements of B are consistent with the conditions for model coherency, while the signs of the estimated parameters for boat, rainbow trout, and salmon indicate positive contribution to utility. Interestingly the sign for the lake trout parameter indicates a negative contribution to utility for increases in the lake trout catch rate. This non-intuitive result is consistent with the findings in the Kuhn-Tucker model, which showed lake trout to be the least preferred species. The estimate of own and cross price effects on notional expenditure are relatively robust to the changes in quality variable specification.

5.2.3 Welfare Analysis

The main dual model was used to evaluate the policy scenarios outlined above, with the exception of scenario D, which is not possible under this specification. The calculations were performed using the procedure outlined in Chapter 3. Specifically,

Table 5.10 A Variation on the Dual Model: Estimation Results

Parameter	Estimate	P-Value
δ_0 (Boat)	0.3964	.006
δ_1 (Chinook Salmon+ Coho Salmon)	17.21	.001
δ_2 (Rainbow Trout)	11.08	.182
δ_3 (Lake Trout)	-15.38	.003
β_{12} (South Lake Michigan/ North Lake Michigan)	-0.2609	.105
β_{13} (South Lake Michigan/ Green Bay)	-0.1693	.1816
β_{14} (South Lake Michigan/ Lake Superior)	-0.2688	.1010
β_{23} (North Lake Michigan/ Green Bay)	0.3113	.0527
β_{24} (North Lake Michigan/ Lake Superior)	-0.2604	.1257
β_{34} (Green Bay/Lake Superior)	-0.8902	.009
σ (Standard Deviation of ε)	2.25	<.001

Table 5.11 A Variation on the Dual Model: Estimates of Own and Cross Price Effects on Notional Shares

	South Lake Michigan	North Lake Michigan	Green Bay	Lake Superior
South Lake Michigan	-0.19	0.07	0.05	0.07
North Lake Michigan	0.07	-0.05	-0.08	0.07
Green Bay	0.05	-0.08	-0.20	0.24
Lake Superior	0.07	0.07	0.24	-0.38

- For each observation in the sample $(n = 1,...,266)$ a total of $N_\varepsilon = 500$ vectors of random disturbances terms (i.e., $\varepsilon^{(nk)}, k = 1,..., N_\varepsilon$) were drawn from the estimated distribution for ε.

- Substituting the maximum likelihood estimates of the parameters from Table 5.7 $(\hat{\gamma})$ and $\varepsilon^{(nk)}$ for γ and ε in equation (3.47), numerical bisection was used to solve for C, with the result labeled $C^{(nk)}$.

- Averaging over the $C^{(nk)}$'s over the N_ε disturbance vectors and N observations in the sample yields a point estimate $\hat{C}$ for average compensating variation in the population, given $\hat{\gamma}$.

An additional step was made in the calculation to account for the fact that both use values and non-use values are present in the estimates of compensating variation. Because policy makers are typically most interested in the use value associated with a resource it was desirable to eliminate non-use values from the estimated welfare effect to measure the use value alone as well as the total value. Non-use values arise in this model from the fact that catch rates for the non-visited sites enter the demand for the visited sites through the

virtual prices. Therefore, for each draw of the error in the Monte Carlo process, the virtual prices for the non-visited sites are computed assuming catch rates for those sites are zero. In this way the demands for the visited sites are functions of only the visited site catch rates and the boat indicator variable, implying welfare calculations will reflect only the use-value associated with the resource. Note also that the Krinsky and Robb confidence interval step is not included in the procedure, implying that the welfare estimates are point estimates conditional on the estimated parameters Confidence intervals were computed for the dual welfare measures, but the small number of data points in the users-only sample did not provide enough precision in the parameter estimates to arrive at policy relevant confidence intervals.

Welfare estimates for the main dual model are presented in Table 5.12. Total values are presented in the first column, while the calculations containing only use values are presented in the second column. The total values are uniformly large, implying large non-use values when compared with the use values in the second column. It is likely these large non-use values result primarily from the structure of the model, which inserts catch rates for the non-consumed goods into the demand for the consumed goods through the virtual prices, rather than from preferences for the resource. Therefore discussion will focus on the use value component of the welfare measures.

Scenarios A and B provide estimates of the average welfare effects of the loss of lake trout and Coho salmon in Lake Michigan, respectively. Great Lakes users would need to be compensated approximately $1700 for the loss of lake trout in Lake Michigan,

Table 5.12 Welfare Estimates for Main Dual Model

Policy Scenario	Mean Compensating Variation	
	Total	Use Only
Scenario A: Loss of Lake Trout in Lake Michigan	5209.30	1705.54
Scenario B: Loss of Coho Salmon in Lake Michigan	6223.89	1031.17
Scenario C: A 20% Increase in Lake Michigan Rainbow Trout	-97.46	-19.77
Scenario D: A 20% Reduction in Toxins in all Sites	*	*
Scenario E: Loss of South Lake Michigan Site	9890.46	1554.09

and approximately $1031 for the loss of Coho salmon. As was noted in the discussion of the welfare effects in the variations of the Kuhn-Tucker model, use of the catch rate index does not allow preferences for the individual species to be reflected in the estimates. The estimates therefore differ due to the magnitude of the catch rates, with catch rates for lake trout in Lake Michigan among the users of the Great Lakes being slightly larger than those for Coho salmon.

Scenario C provides an example of a willingness to pay estimate in the dual model, in this case for an increase in rainbow trout catch rates in Lake Michigan. The estimate is significantly smaller than the willingness to accept estimates. This is not unexpected, since willingness to pay is a budget constrained measure, while willingness to accept is not. Under the weak separability assumption of this model, willingness to pay is constrained by the recreation budget, leading to the relatively small average estimate of $19.77 for the scenario benefits.

The final scenario measures the damage per angler of the loss of the South Lake Michigan site. Almost $1555 per season would be needed to compensate anglers for this type of damage to the resource.

5.3 Estimation of a Competing Framework

Herriges, Kling, and Phaneuf (1997), in a comparison of competing frameworks for corner solutions in recreation demand, estimate several versions of the linked site selection and participation models. The various versions produce model fits of varying quality, and parameter and welfare estimates of varying orders of magnitude. For completeness, the results from the most reasonable of these versions are presented here.

For the site selection component of the model a linear utility function is assumed, defined as

$$V_j = \beta_1(y - p_j) + \beta_2 CAT_j + \beta_3 E_j + \varepsilon_j, \quad j = 1,...,4, \tag{5.1}$$

where y is monthly income, CAT_j and E_j are catch rate index and effective toxin level variables, and ε_j is a generalized extreme value variate, implying the site selection model is nested logit.[8] The North and South Lake Michigan sites are contained in one nest, and Lake Superior and Green Bay in the other. The estimated parameters for the site selection model are presented in Table 5.13. All the coefficients are of the expected sign, and θ lies in the $(0,1)$ interval, implying the RUM model is consistent with utility theory. The standard error on $\hat{\theta}$ is 0.011, implying that the estimate is significantly different from one and that the straight multinomial logit specification is rejected.

The participation equation is also assumed to be linear, defined as

$$T = \delta_0 + \delta_1 PI + \delta_2 B + \delta_3 Y + \mu, \tag{5.2}$$

where PI is the price index (inclusive value) defined in equation (2.4) and used by Bockstael, Hanemann, and Kling (1987), B is the boat indicator variable, and Y is annual income. The model was estimated using the Tobit procedure, with results presented in Table 5.14. The results are generally significant, although the negative sign on annual income indicates recreation fishing trips are an inferior good.

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[8] Herriges, Kling, and Phaneuf use a catch rate index that is different than defined above, and use slightly fewer observations. The index is calculated as the sum of the species-specific catch rates, weighted by dummy variables indicating whether or not the angler targeted that species of fish. The results presented here use their catch rate index, and the entire sample of individuals.

Table 5.13 Competing Framework: Site Selection Estimates

Parameter	Estimate	P-Value
β_1 (Marginal Utility of Income)	242.64	<.001
β_2 (Catch Rate Index)	4.957	<.001
β_3 (Toxins)	-0.133	<.001
θ	0.976	<.001

Table 5.14 Competing Framework: Tobit Participation Estimates

Parameter	Estimate	P-Value
δ_0 (Intercept)	-9.86	<.001
δ_1 (Price Index)	0.035	.011
δ_2 (Boat)	25.10	<.001
δ_3 (Annual Income)	-0.00293	.010
σ (Standard Error of ε)	25.45	<.001

Table 5.15 Competing Framework: Welfare Estimates

Policy Scenario	Welfare Estimate
Scenario B: Loss of Coho Salmon in Lake Michigan	263.91
Scenario D: A 20% Reduction in Toxins in all Sites	-170.51
Scenario E: Loss of South Lake Michigan Site	2000.26

Welfare calculations are performed using the Creel and Loomis (1992) variation on the Bockstael, Hanemann, and Kling approach. Point estimates for three of the policy scenarios were computed and are presented in Table 5.15 above.

5.4 Comparison and Discussion

In the previous three sections estimation and welfare calculations are presented for the three approaches to solving the corner solution problem discussed in this thesis. The parameter estimates between the three approaches are not directly comparable, but the models are used to evaluate the same welfare scenarios, for which the estimates can be compared. Of the three approaches, the Kuhn-Tucker model appears to deliver the best overall empirical performance. The model is reasonably robust to changes in specification.[9] For example, the estimates for scenarios D and E, which do not involve changes in the catch rates, are stable across all three specifications presented. For the main model and variation A, which both include species-specific catch rates, welfare estimates involving the catch rate changes are of the same order of magnitude. It is only when the catch rate index is used that scenarios A, B, and C vary significantly from the main model. As noted above, this highlights the importance of accounting for variation in preferences for species in some situations. In cases where there are not large differences in preferences for species, the aggregate catch rate may be a reasonable specification that eases the burden of estimation. Due in part to the choice of error structure, the Kuhn-

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[9] It also appears to be relatively robust to changes in the number of observations included. Herriges, Kling and Phaneuf include in their estimation of the Kuhn-Tucker model only anglers who made less then 50 trips during the season and report similar welfare estimates.

Tucker model is relatively easy to estimate in comparison to the dual model. Robustness

of the estimation results to changes in the error assumption would help justify the original,

convenient error distribution assumption. Although it is not a formal test, it appears that

similar estimation results can be obtained from assuming the errors are normally

distributed.

Because they are equivalent from the point of view of consumer choice theory, the

dual model can be viewed as a generalization of the Kuhn-Tucker model, since it uses a

second order approximation indirect utility function and more general error structure. In a

perfect experiment the same observations and quality variables would be used in both

estimations, providing a consistent baseline for comparison and a means for testing the

sensitivity of results to the choice of utility function. The assumption of weak separability

used in the dual estimation, however, precludes direct comparison with the Kuhn-Tucker

model, since welfare calculations include only the effects of users of the Great Lakes. The

more challenging estimation process also prevents a direct comparison, since the dual

model does not include the toxin variable and the catch rate index is employed, along with

its above mentioned shortcomings. Nonetheless, to provide a rough comparison, the

welfare estimates from the Kuhn-Tucker model can be computed including only the users

of the resource. Given these rough estimates, the dual model compares reasonably

favorably with the Kuhn-Tucker. For example, using the main model parameter estimates

and including only the 266 Great Lakes users in the welfare calculation procedure, the

welfare loss for eliminating Coho salmon from Lake Michigan is approximately $500,

while the estimated welfare loss for the elimination of the South Lake Michigan site is

approximately $940. A better comparison can be made using variation B (catch rate index variation) of the Kuhn-Tucker model and the 266 resource users. Welfare losses for the Coho experiment and the site loss experiment in this case are approximately $806 and $1320, respectively. These estimates are smaller than those resulting from the dual model, but on the same order of magnitude. In addition, the sign of the difference in the estimates is consistent with LaFrance's (1993) prediction on the bias in welfare measures due to the assumption of weak separability. For a willingness to accept measure, LaFrance shows a weak separability model will tend to overestimate the amount of money necessary to compensate consumers for a damage to the resource. This is an intuitive result, since under the assumption of weak separability consumers are not able to substitute between expenditures on recreation and expenditures on all other goods, therefore requiring more in compensation to maintain utility. In spite of the difficulties with the use of the dual approach, the results here seem to indicate it has potential for successful use in other applications, while the rough robustness of the welfare estimates to those resulting from the Kuhn-Tucker model may justify the use of the relatively restrictive forms for the utility function and error distribution in the Kuhn-Tucker model.

Interestingly, the welfare estimates resulting from the linked model presented in Section 5.3 are of a reasonable order of magnitude, perhaps indicating that the ease of its estimation justifies its use as a good approximation to the utility consistent, more difficult to implement models. As is discussed in detail in Herriges, Kling, and Phaneuf (1997), however, the various options for implementing the linked model produce widely varying parameter and welfare estimates, often of non-intuitive magnitudes and signs. Given that

none of the approaches are derived in a utility theoretic framework, the analyst must choose which to implement in an ad hoc manner. Finally, the ease of estimation of the linked models becomes less of an advantage over the Kuhn-Tucker and dual models when the assumptions driving the models are changed. For example, if the site selection model is assumed to be probit rather than nested logit, the same challenges to estimation in terms of evaluating multidimensional normal probabilities are present as in the dual model. Also, if the utility function is assumed to be non-linear in the income term, numerical methods similar to those in the utility-consistent models are needed to conduct welfare analysis in the linked models.

In fairness to the linked model, it should be noted that it was possible to aggregate the destinations in the Great Lakes data into sites in a logical manner that did not result in the loss of characteristics unique to individual sites. This in essence makes the Great Lakes data ideal for estimating models where aggregation is necessary, and makes a primary advantage of the use of the linked models, the ability to handle a large number of unique sites, unnecessary.

CHAPTER 6: SUMMARY AND CONCLUSIONS

This dissertation has examined general corner solution models of consumer choice as they apply to recreation demand, with an emphasis on utility consistent approaches. The methods discussed are of interest not only to those working in recreation demand and resource valuation, but also to researchers working in consumer choice problems where the use of household level data is common. Two utility consistent models based on the Kuhn-Tucker and dual approaches are estimated, and welfare calculations are provided for each. The advantage of these approaches is that they are each derived in an internally consistent manner resulting from a single utility maximization process, simultaneously addressing which of the available sites are visited and how many total trips are made components of the recreation decision. The resulting welfare estimates therefore have a strong theoretical underpinning. These initial applications to the recreation demand literature are presented as an alternative to established approaches to modeling corner solutions, which are derived in an intuitive, although not entirely utility theoretic manner.

The two approaches have been applied to a common data set on recreational fishing in the Wisconsin Great Lakes region, with the Kuhn-Tucker model providing results which conformed best to prior expectations. The model provides intuitive parameter estimates and interpretations, statistically significant welfare estimates of reasonable magnitudes, and is robust to changes in quality attribute specification. It is shown that the Great Lakes fishery has associated with it non-use value, although use value is shown in all variations of the model to account for the majority of total value.

The more difficult to implement dual model was estimated under the assumption that recreation goods are weakly separable in utility. The model provided parameter estimates which were generally consistent with prior expectations, and, particularly for the estimates of own and cross price effects on notional expenditure shares, robust to changes in quality variable specification. Point estimates of use-only welfare effects were of reasonable magnitude and compared favorably to the Kuhn-Tucker model, when consideration is given to the fact that the dual approach included only users of the Great Lakes fishery. Total welfare effect estimates were, unfortunately, of several orders of magnitude larger than was expected a priori. This seems to result more from the structure of the dual model than from the true underlying values in the population. In addition, standard errors on the welfare measures indicated the point estimates are not statistically significant, most likely due to the small number of observations used in the estimation. Nonetheless the dual model performed sufficiently well to warrant cautious optimism in its ability to eventually provide a merging of a second order approximation utility function and a utility consistent corner solution approach in recreation demand.

The welfare calculations resulting from the Kuhn-Tucker and dual model are compared to those from a version of the linked site selection and participation model. The linked models have the advantage of being easy to implement, relying on established econometric techniques and, as they have been presented, providing easy to calculate welfare measures. While the welfare results presented here are of reasonable signs and magnitudes, in a more complete treatment of the various methods available to analysts Herriges, Kling, and Phaneuf (1997) show, using the Wisconsin data, widely ranging

estimates for the policy scenarios described above. Given that none of the linked methods are derived in a utility consistent manner, it is not clear which of the approaches is correct. It is also worth noting that the ease of implementation of the linked model is due in part to relatively restrictive assumptions on the error distribution in the site selection model, and the assumption of a linear income effect. If the model is generalized to include normal errors and non-linear income effects, many of the advantages of the linked model no longer apply. Nonetheless, we should not immediately conclude that the utility consistent models are uniformly preferred to the linked models. Although the utility consistent models, particularly the Kuhn-Tucker model, perform better in this application, in other applications the linked model may be the better choice. In situations were there are many unique destinations, the loss of utility consistency may be offset by the increased richness of the model due to the variation in available sites.

Compared to the linked models appearing in the literature to date, the Kuhn-Tucker and dual models are difficult to estimate and require computer intensive numerical methods for the computation of welfare effects. However, the presence of ever faster and cheaper computers, as well as improved simulation estimation techniques for the evaluation of multidimensional normal probabilities and other econometric advances, should decrease the burden of their use and prompt further applications.

There are many opportunities for future applications to improve on the models presented here. Within the context of the Kuhn-Tucker model it would be interesting to investigate other functional forms for the utility function and pursue further the assumption of normal errors. The trade off, of course, is more complicated Jacobian

transformation terms and estimation process. The dual model, with the possibility of using a flexible functional form for the utility function, has the most potential and also the most difficulties associated with its use. An obvious improvement would be to relax the assumption of weak separability and include a numeraire good, allowing substitution between spending on recreation and other goods as well as incorporating the effects of non-users of the resource. This would allow a direct comparison with the Kuhn-Tucker model to determine its robustness to the choice of utility function and error distribution assumptions. Should the inclusion of a numeraire good prove intractable, a reasonable approach may be to endogenize recreation spending by estimating both stages of the utility maximization process. In this case the dual approach would proceed similar to the linked models, with the advantage that the separate estimates are linked in a utility consistent, two-stage budgeting manner. Another structural improvement would be to better account for non-use values in the model. Perhaps a functional form can be discovered which is both sufficiently flexible and provides an opportunity to structurally impose and/or test for weak complementarity. Finally, specifications allowing the use of the toxin variables and individual catch rates should be further explored.

Econometrically the dual model can be improved by fully estimating the variance/covariance matrix. This is tedious but not impossible to program in GAUSS. A greater number of observations, however, would be necessary than are available for this study to effectively estimate the extra parameters. A larger number of observations may also provide enough precision in the estimated parameters to effectively implement the Krinsky and Robb procedure for computing confidence intervals.

An interesting enhancement to either of the utility-consistent models would be to better account for the opportunity cost of time, rather than simply assuming a fraction of the wage rate. Since labor supply studies are basically extreme corner solution models, a natural extension of recreation corner models is to model the labor/leisure choice as well. In such a model the shadow value of time would be endogenous to the model, and would depend on the characteristic of the individual (i.e. wage earner with the possibility of exchanging time for money versus a fixed hours salaried individual who cannot).

Finally, the models and techniques used here can be adapted for use in other consumer choice problems. The increasing availability of household level data requires the use of operational techniques for dealing with corner solutions. Consumer demands can be modeled using either the Kuhn-Tucker or dual approach, and Monte Carlo methods similar to those used for welfare calculations can be designed to calculate elasticities or other measures of interest.

APPENDIX

The purpose of this appendix is to formally describe the reasoning behind the decomposition of total compensating variation into "use" and "non-use" components as presented in Tables 5.5, 5.6, and 5.7. In order to simplify the exposition, we abstract from the general corner solution problem by assuming an interior solution. The generalization to cases in which corner solutions emerge is straightforward, but tedious, and adds nothing to the intuition. In addition, the presentation is simplified by considering a simple two good problem.

To understand the calculation of use and non-use values in scenarios A-D, consider the problem of measuring the total compensating variation associated with changing the attribute of site 2 from q_2^0 to q_2^1, without changing the corresponding characteristics of site 1. This total compensating variation can be expressed in terms of expenditure functions as

$$C_{total} = e(p^0, q_1^0, q_2^0, U^0) - e(p^0, q_1^0, q_2^1, U^0), \qquad (A1)$$

where p_j^0 denotes the initial cost of visiting site j and U^0 denotes the individual initial level of utility. In the absence of weak complementarity, this total value can be divided into two components: use value and non-use value. The following definition of non-use value is used.

$$C_{non-use} = e(p_1^0, p_2^*, q_1^0, q_2^0, U^0) - e(p_1^0, p_2^*, q_1^0, q_2^1, U^0), \qquad (A2)$$

where p_j^* denotes the choke price associated with site j. Thus, we define non-use value to be the compensating variation an individual consumer places on the change in

environmental quality when the consumer does not consume any of the good whose

quality changes. To derive an expression for the resulting use value it is only necessary to

subtract non-use value in (A2) from the total value in (A1) yielding

$$
\begin{aligned}
C_{use} &= C_{total} - C_{non-use} \\
&= e(p_1^0, p_2^0, q_1^0, q_2^0, U^0) - e(p_1^0, p_2^0, q_1^0, q_2^1, U^0) - \\
&\quad e(p_1^0, p_2^\bullet, q_1^0, q_2^0, U^0) - e(p_1^0, p_2^\bullet, q_1^0, q_2^1, U^0) \\
&= \int_{p_2^0}^{p_2^\bullet} h_2(p_1^0, p_2, q_1^0, q_2^1, U^0) dp_2 - \int_{p_2^0}^{p_2^\bullet} h_2(p_1^0, p_2, q_1^0, q_2^0, U^0) dp_2.
\end{aligned} \tag{A3}
$$

As is clear from the expression in the third line of (A3), this definition of use value

corresponds to the sum of the areas under the Hicksian demand curves for the good

whose quality changes.

Calculation of the use and non-use components for the elimination of a site as in

scenario E proceeds differently. The use component of total value corresponds to the

total area under the Hicksian demand curve. That is,

$$
C_{use} = \int_{p_2^0}^{p_2^\bullet} h_2(p_1^0, p_2, q_1^0, q_2^0, U^0) dp_2, \tag{A4}
$$

where $p_2^\bullet$ is the choke price for site 2. This is analogous to equation (A3), although a

movement along rather than a shift in the demand curve is considered.

With $\theta \neq 1$, the specification of the utility function implies there is still value from

the site with all use eliminated. This results from the fact that the quality index for the site

still enters the utility function positively. Assuming that the elimination of the site also

eliminates the factors entering the quality index, to calculate the total welfare loss it is

necessary to eliminate the effect of the quality index on utility. This is accomplished by setting $\theta = 1$ for the component of the utility function in equation (3.1) corresponding to the eliminated site and proceeding with the welfare calculations as described in the text. For the remaining components of the utility function θ remains the same, preserving the non-use value among the sites that are still available.

REFERENCES

Amemiya, T., "Multivariate Regression and Simultaneous Equation Models When the Dependent Variables are Truncated Normal," *Econometrica* 42 (1974), 999-1012.

Bain, L.J. and M. Engelhardt, *Introduction to Probability and Mathematical Statistics*, Boston, MA: PWS-Kent Publishing Company, 1992.

Bockstael, N.E., W.M. Hanemann, and C.L. Kling, "Estimating the Value of Water Quality Improvements in a Recreation Demand Framework," *Water Resources Research* 23 (1987), 951-60.

Bockstael, N.E., W.M. Hanemann, and I.E. Strand, *Measuring the Benefits of Water Quality Improvements Using Recreation Demand Models*, Vol. 2, Washington, D.C.: U.S. Environmental Protection Agency, Office of Policy Analysis, 1986.

Bockstael, N.E., K.E. McConnell, and I.E. Strand, "Recreation," in *Measuring the Demand for Environmental Quality*, J. Brandon and C. Kolstad, eds., New York, NY: Elsevier Publishers, 1991.

Bockstael, N.E. and I.E. Strand, "The Effect of Common Sources of Regression Error on Benefit Estimates," *Land Economics* 63 (1987),11-20.

Bockstael, N.E., I.E. Strand and W.M. Hanemann, "Time and the Recreational Demand Model," *American Journal of Agricultural Economics* 69 (1987), 11-20.

Bockstael, N.E., I.E. Strand, K.E. McConnell, and F. Arsanjani, "Sample Selection Bias in the Estimation of Recreation Demand Functions: An Application to Sportfishing," *Land Economics* 66 (1990), 40-49.

Brown, W.G., and F. Nawas, "Impact of Aggregation on the Estimation of Outdoor Recreation Demand Functions," *American Journal of Agricultural Economics* 55 (1973), 246-249.

Caulkins, P., R. Bishop, and N. Bouwes, "The Travel Cost Model for Lake Recreation: A Comparison of Two Methods for Incorporating Site Quality and Substitution Effects," *American Journal of Agricultural Economics* 68 (1986), 291-297.

Chiang, J., "A Simultaneous Approach to the Whether, What and How Much to Buy Questions," *Market Science* 10 (1991), 297-315.

Chiang, J. and L.F. Lee, "Discrete/Continuous Models of Consumer Demand with Binding Non-negativity Constraints," *Journal of Econometrics* 54 (1992), 79-93.

Christensen, L.R., D.W. Jorgenson, and L.J. Lau, "Transcendental Logarithmic Utility Functions," *American Economic Review* 65 (1975), 367-383.

Creel, M., and J.B. Loomis, "Theoretical and Empirical Advantages of Truncated Count Data Estimators for Analysis of Deer Hunting in California, *American Journal of Agricultural Economics* 72 (1990), 434-45.

De Vault, D.S., R. Hesselberg, P.W. Rodgers and T.J. Feist, "Contaminant Trends in Lake Trout and Walleye from the Laurentian Great Lakes," *Journal of Great Lakes Research* 22 (1996), 884-895.

De Vault, D.S., D. Dunn, P. Bergqvist, K. Wiberg and C. Rappe, "Polychlorinated Dibenzofurans and Ploychlorinated Dibenzo-p-Dioxins in Great Lakes Fish: A Baseline and Interlake Comparison," *Environmental Toxicology and Chemistry* 8 (1989), 1013-1022.

Durrett, R., *Probability: Theory and Examples*, Belmont, CA: Wadsworth Publishing Company, 1996.

Edgerton, D.L., "Weak Separability and Demand Estimation,", *American Journal of Agricultural Economics*, 79 (1997), 62-79.

Feather, P., D. Hellerstein, and T. Tomasi, "A Discrete-Count Model of Recreation Demand," *Journal of Environmental Economics and Management* 30 (1996), 316-322.

Fortin, B. and G. Lacroix, "Labor Supply, Tax Evasion and the Marginal Cost of Public Funds - An Empirical Investigation," *Journal of Public Economics* 55 (1994), 407-431.

Freeman, A. M., *The Measurement of Environmental and Resource Values: Theory and Methods*, Washington, D.C.: Resources for the Future, 1993.

Gelman, A., J.B. Carlin, H.S. Stern, and D.B. Rubin, *Bayesian Data Analysis*, London: Chapman and Hall, 1995.

Geweke, J., "Monte Carlo Simulation and Numerical Integration," in *Handbook of Computational Economics*, H. Amman, D. Kendrick, and J. Rust, eds., Amsterdam: Elsevier Science B.V., 1996.

Hanemann, W.M., *A Methodological and Empirical Study of the Recreation Benefits from Water Quality Improvement*, Ph.D. dissertation, Department of Economics, Harvard University, 1978.

Hanemann, W.M., "Welfare Evaluations in Contingent Valuation Experiments with Discrete Responses," *American Journal of Agricultural Economics* 66 (1984a), 332-341.

Hanemann, W. M., "Discrete-Continuous Models of Consumer Demand," *Econometrica* 52 (1984b), 541-561.

Hausman, J.A., G.K. Leonard, and D. McFadden, "A Utility-Consistent, Combined Discrete Choice and Count Data Model: Assessing Recreational Use Losses Due to Natural Resource Damage," *Journal of Public Economics* 56 (Winter 1995), 1-30.

Hellerstein, D., "Welfare Estimation Using Aggregate and Individual-Observation Models: A Comparison Using Monte Carlo Techniques," *American Journal of Agricultural Economics* 77 (1995), 620-630.

Hellerstein, D. and R. Mendelsohn, "A Theoretical Foundation for Count Data Models," *American Journal of Agricultural Economics* 75 (1993), 604-611.

Herriges, J. A., and C. L. Kling, "Testing the Consistency of Nested Logit Models with Utility Maximization," *Economics Letters* 50 (1996), 33-39.

Herriges, J. A., and C. L. Kling, "Nonlinear Income Effects in Random Utility Models," working paper, Iowa State University, October 1997.

Herriges, J.A., C.L. Kling, and D.J. Phaneuf, "Corner Solution Models of Recreation Demand: A Comparison of Competing Frameworks," forthcoming in *Valuing the Environment Using Recreation Demand Models*, J.A. Herriges and C.L. Kling, eds., Aldershot, U.K.: Edward Elgar, 1998.

Hewitt, J.A. and W.M. Hanemann, "A Discrete/Continuous Choice Approach to Residential Water Demand under Block Rate Pricing," *Land Economics* 71 (1995), 173-192.

Kaoru, Y., V.K. Smith, and J.L. Liu, "Using Random Utility Models to Estimate the Recreational Value of Estuarine Resources," *American Journal of Agricultural Economics*, 77 (1995), 141-151.

Kealy, M.J. and R.C. Bishop, "Theoretical and Empirical Specification Issues in Travel Cost Demand Studies," *American Journal of Agricultural Economics* 68 (1986), 660-667.

Kling, C.L., "Comparing Welfare Estimates of Environmental Quality Changes from Recreation Demand Models," *Journal of Environmental Economics and Management* 15 (1988), 331-340.

Kling, C.L., "The Importance of Functional Form in the Estimation of Welfare," *Western Journal of Agricultural Economics* 14 (1989), 168-174.

Kling, C.L. and J.R. Crooker, "Recreation Demand Models for Environmental Valuation," forthcoming in *The Handbook of Environmental and Resource Economics*, J. van den Bergh, ed., Aldershot, U.K.: Edward Elgar, 1998.

Kling, C.L. and J.A. Herriges, "An Empirical Investigation of the Consistency of Nested Logit Models with Utility Maximization," *American Journal of Agricultural Economics* 77 (1995), 875-884.

Kling, C.L. and C.J. Thomson, "The Implications of Model Specification for Welfare Estimation in Nested Logit Models," *American Journal of Agricultural Economics* 78 (1996), 103-114.

Krinsky, I., and A. Robb, "On Approximating the Statistical Properties of Elasticities," *Review of Economics and Statistics* 68 (1986), 715-719.

Lacroix, G., and B. Fortin, "Utility-Based Estimation of Labor Supply Functions in the Regular and Irregular Sectors," *Economic Journal* 102 (1992), 1407-1422.

LaFrance, J.T., "Weak Separability in Applied Welfare Analysis," *American Journal of Agricultural Economics* 75 (1993), 770-775.

Larson, D., "Separability and the Shadow Value of Leisure Time," *American Journal of Agricultural Economics* 75 (1993a), 572-577.

Larson, D., "Joint Recreation Choices and Implied Values of Time," *Land Economics* 69 (1993b), 270-86.

Larson, D.M., S.L. Shaikh, and J.B. Loomis, "A Two-Constraint AIDS Model of Recreation Demand," working paper, 1997.

Lee, L.F., and M.M. Pitt, "Microeconometric Demand Systems with Binding Nonnegativity Constraints: The Dual Approach," *Econometrica* 54 (1986a), 1237-42.

Lee, L. F., and M.M. Pitt, "Specification and Estimation of Consumer Demand with Many Binding Non-Negativity Constraints," Center for Economic Research Discussion Paper No. 236, Department of Economics, University of Minnesota, 1986b.

Lee, L.F., and M.M. Pitt, "Microeconometric Models of Rationing, Imperfect Markets, and Non-Negativity Constraints," *Journal of Econometrics* 36 (1987), 89-110.

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

Maler, K., *Environmental Economics*, Baltimore: Johns Hopkins, 1974.

McConnell, K.E., "On-Site Time in the Demand for Recreation," *American Journal of Agricultural Economics* 74 (1992), 918-925.

McConnell, K.E., and I.E. Strand, "Measuring the Cost of Time in Recreation Demand Analysis: An Application to Sport Fishing," *American Journal of Agricultural Economics* 63 (1981), 153-156.

McFadden, D.L., "Econometric Models of Probabilistic Choice," in *Structural Analysis of Discrete Data*, C.F. Manski and D.L. McFadden, eds., Cambridge, MA: MIT Press, 1981.

McFadden, D.L., "Computing Willingness-to-Pay in Random Utility Models," working paper, Department of Economics, University of California-Berkeley, December 1995.

Morey, E.R., "The Choice of Ski Areas: Estimation of a Generalized CES Preference Ordering with Characteristics, Quadratic Expenditure Functions, and Non-Additivity," *Review of Economics and Statistics* 66 (1984), 221-36.

Morey, E.R., "Two RUMs UnCLOAKED: Nested-Logit Models of Site Choice and Nested-Logit Models of Participation and Site Choice," forthcoming in *Valuing the Environment Using Recreation Demand Models*, J.A. Herriges and C.L. Kling, eds., Aldershot, U.K.: Edward Elgar, 1998.

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

Morey, E.R., D. Waldman, D. Assane, and D. Shaw, "Specification and Estimation of a Generalized Corner Solution Model of Consumer Demand: An Amemiya-Tobin Approach," working paper, University of Colorado-Boulder, May 1990.

Morey, E.R., 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.

Parsons, G.R., and M.J. Kealy, "Randomly Drawn Opportunity Sets in a Random Utility Model of Lake Recreation," *Land Economics* 68 (1992), 93-106.

Parsons, G.R., and M.J. Kealy, "A Demand Theory for Number of Trips in a Random Utility Model of Recreation," *Journal of Environmental Economics and Management* 29 (1996), 418-433.

Parson, G.R. and M.S. Needelman, "Site Aggregation in a Random Utility Model of Recreation," *Land Economics* 68 (1992), 418-433.

Ransom, M.R., "The Labor Supply of Married Men - A Switching Regressions Model," *Journal of Labor Economics* 5 (1987a), 63-75.

Ransom, M.R., "An Empirical Model of Discrete and Continuous Choice in Family Labor Supply," *Review of Economics and Statistics* 69 (1987b), 465-472.

Small, K.A. and H.S. Rosen, "Applied Welfare Economics with Discrete Choice Models," *Econometrica* 49 (1981), 105-130.

Smith, V. K., "Combining Discrete Choice and Count Data Models: A Comment," working paper, 1997.

Smith, V.K., W.H. Desvousges, and M.P. McGivney, "The Opportunity Coat of Travel Time in Recreation Demand Models," *Land Economics* 59 (1983), 259-277.

Srinivasan, T.C., *Corner Solution Approaches to Modeling Choice*, Ph.D. dissertation, Department of Management, Vanderbilt University, 1989.

Srinivasan, T.C. and R.S. Winer, "Using Neoclassical Consumer-Choice Theory to Produce a Market Map From Purchase Data," *Journal of Business and Economic Statistics* 12 (1994), 1-9.

Tobin, J., "Estimation of Relationships for Limited Dependent Variables, *Econometrica* 26 (1958), 24-36.

Tong, T.L., *The Multivariate Normal Distribution*, New York, NY: Springer-Verlag, 1990.

Van Soest, A. and P. Kooreman, "Coherency of the Indirect Translog Demand System with Binding Non-negativity Constraints," *Journal of Econometrics* 44 (1990), 391-400.

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

Yen, S. T., and W. L. Adamowicz, "Participation, Trip Frequency, and Site Choice: A Multinomial Poisson Hurdle Model of Recreation Demand," *Canadian Journal of Agricultural Economics* 42 (1994), 65-76.

Yen, S.T., and T.L. Roe, "Estimation of a 2-Level Demand System with Limited Dependent-Variables," *American Journal of Agricultural Economics* 71 (1989), 85-98

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