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Using Partial Site Aggregation to Reduce Bias in Random Utility Travel Cost Models

Frank Lupi and Peter M. Feather

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East Lansing , Michigan

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by

Frank Lupi
Department of Agricultural Economics
Michigan State University
East Lansing, MI 48824-1039

and

Peter M. Feather
Economic Research Service, USDA
1301 New York Ave. NW, Room 538a
Washington, DC 20005-4788

July, 1997

Using Partial Site Aggregation to Reduce Bias in Random Utility Travel Cost Models

ABSTRACT

We propose a "partial aggregation" strategy for defining the recreation sites that enter choice sets in random utility models. Under the proposal, the most popular sites and sites that will be the subject of policy analysis enter choice sets as individual sites while remaining sites are aggregated into groups of similar sites. The scheme balances the desire to include all potential substitute sites in the choice sets with practical data and modelling constraints. Unlike fully aggregate models, our analysis and empirical applications suggest that the partial aggregation approach reasonably approximates the results of a disaggregate model. The partial aggregation approach offers all of the data and computational advantages of models with aggregate sites, but does not suffer from the same degree of bias as fully aggregate models.

Introduction

The random utility model (RUM) is a popular variant of the travel-cost method for estimating the demand for recreation sites [see *Bockstael et al.*].¹ One strength of the RUM is its ability to relate the demand for water-based recreation at a site to the water quality at that site. This linkage allows the RUM to be used to estimate the use-values associated with changes in water quality at specific sites. Such nonmarket benefits are increasingly utilized in policy making, project evaluation and environmental legislation.² Another advantage of the RUM is that it provides a tractable way of including the prices and qualities of substitute recreation sites in the demand function. This feature of the RUM is important for benefit estimation because water-based recreation sites often have numerous substitutes and these substitution possibilities affect the magnitude of benefit measures.

An underlying postulate of the RUM is that individuals will choose to visit the recreation site that gives them the highest utility. To estimate the model researchers must specify the set of mutually exclusive alternatives from which an individual makes a choice. This set of alternatives (recreation sites) is referred to as the choice set. In the case of water-based recreation, when all potential substitute sites are considered the choice set can become extremely large. Choice sets containing hundreds of alternatives can pose substantial computational burdens for the estimation of a RUM and can stretch the limits of the available data. Reductions in the size of the choice set are usually achieved by limiting the scope of the model or by spatially aggregating alternatives. This paper addresses the issue of whether alternatives in the choice set are defined as individual sites or as aggregate groups of sites.

¹ Early applications of the RUM in the area of water-based recreation demand include *Hanemann* [1978], *Feenberg and Mills* [1980], *Caulkins et al.* [1986], and *Bockstael et al.* [1987].

² The Comprehensive Environmental Responses, Compensation and Liability Act (CERCLA), the Oil Pollution Act, the National Forest Management Act, and the Environmental Protection Agency's guidelines for regulatory impact analysis [U.S. EPA] all use nonmarket benefit measurement in some manner.

The use of aggregate representations of sites is common in the RUM literature.³ *Bockstael et al.* [1989] explain that for most models, the potentially hundreds or thousands of specific sites cannot be modelled and must be aggregated, especially when data is sparse [page 252]. Several authors have pointed out that aggregate alternatives make efficient use of the behavioral data by increasing the number of visits to the each of the alternatives [see *Morey et al.*, 1993; *Morey and Shaw*, 1990].⁴ Table 1 presents a summary of RUMs that have used some type of aggregation of sites. In several cases, researchers have defined sites to match existing levels of aggregation in the data that describes sites [see *Kling and Thomson*; *Jones and Sung* 1993; *Lin et al.* 1996]. From Table 1, the most common way to group sites is to define them at the county level.

An interesting alternative to aggregating sites at the county level is to specify sites at differing degrees of spatial resolution. *Carson and Hanemann* [1987] define sport fishing sites in southcentral Alaska so that some smaller and less popular sites within the southcentral region are aggregated and all sites outside of the southcentral region are grouped into four other broadly defined alternatives. In a model of salmon fishing, *Morey et al.* [1993] examine the effects of various hydropower regimes on the Penobscot River in Maine. In their RUM, the Penobscot River is treated as an individual site while remaining rivers in Maine are grouped into four alternatives, and rivers in Canada are grouped at the level of provinces. *Hausman et al.* [1995] developed recreation demand models to assess the damages of the *Exxon Valdez* spill. They define sites so that they are "highly disaggregated" in areas near the spill and "quite broad"

³ The literature on travel cost models has used the term aggregation in several confounding ways. Here we use the term aggregation to refer to the grouping of individual sites into larger sites. This usage follows the terminology set forth in *McFadden* [1978], *Ben-Akiva and Lerman* [1985], and *Parsons and Needelman* [1992], among others. We are not referring to the estimation and welfare implications of using of aggregate versus individual observations of recreation behavior (see *McConnell and Bockstael* [1984] for a discussion of these issues).

⁴ While the share model of *Morey and Shaw* [1990] is not strictly a RUM, it is statistically similar and requires researchers to define sites.

further from the spill. We will refer to this practice as "partially aggregating" sites. The focus of this paper is to investigate the performance of this strategy using RUMs. The appeal of the approach is that it allows the analysis to focus on potentially more important sites without excluding plausible substitutes. The downside is that *McFadden* [1978] has shown that using aggregate alternatives can lead to biased estimates of the RUM parameters.

The potential bias due to aggregating water-based recreation sites has been empirically examined by *Kaoru and Smith* [1990], *Parsons and Needelman* [1992], and *Feather* [1994]. All of these studies compare models in which all sites are aggregated to models with none of the sites being aggregated. *Kaoru and Smith* [1990] (see also *Kaoru et al.* [1995]) estimated several RUMs to determine the benefits of improved water quality in a North Carolina sport fishing estuary. They used three different levels of aggregation, and their findings suggest that increasing levels of site aggregation tended to lead toward an understatement of benefits. The opposite conclusion was reached by *Feather* [1994] in a study contrasting aggregated and disaggregated RUMs. This coincides with the findings of a study conducted by *Parsons and Needelman* [1992] where benefits and the degree of site aggregation are positively correlated. Although these studies have all dealt with aggregated models, none of them provide any guidance as to the effect of aggregation (or partial aggregation) on benefit estimates. This paper sheds some light on these issues.

As an alternative to aggregating sites, *McFadden* [1978] proposed reducing RUM choice sets by estimating the models using randomly drawn choice sets. This approach has been studied by *Parsons and Needelman* [1992], *Feather* [1994], and *Peters et al.* [1995]. The random draw approach is often favored over aggregation because it results in consistent, though inefficient, estimates of the RUM parameters [*McFadden*, 1978]. Unfortunately, the consistency of random sampling strategies has only been demonstrated for the simple multinomial logit form

of the RUM, not the more general nested logit.⁵ Moreover, the random draw procedure itself does not alleviate computational problems. Because the parameters from models estimated using random draws vary with each draw, most researchers have suggested estimating several models using different draws [*Parsons and Needelman* 1992; *Feather* 1994].⁶ Clearly the process of repeating the random draws can be cumbersome. While there are advantages of using random draws, most RUMs in the literature do not utilize the technique.

The following section reviews the theory of site aggregation in RUMs and presents the partially aggregated model. Next, the potential bias in welfare measures attributed to aggregated and partially aggregated models is discussed. This is followed by an empirical application of sport fishing at lakes in Minnesota. Welfare measures from a disaggregated model are then compared to those computed using aggregated and partially aggregated models. The results demonstrate the potential for using partial aggregation to dramatically reduce the number of alternatives in the RUM without greatly compromising accuracy.

RUMs Under Varying Levels of Aggregation

The actual discrete alternatives in an individual's choice set are commonly referred to as "elemental alternatives" [*Ben-Akiva and Lerman*, 1985]. In the case of water-based recreation,

⁵ One alternative for nested logits is to draw random samples from each nest and then employ a sequential estimation strategy. Even if a full information, random draw estimation strategy for nested logits were demonstrated, it would not resolve estimation issues related to choice set size for more general error distributions such as multinomial probit.

⁶ *Waters and Deitz* [1996] present a stability criteria for determining how many times to repeat the random draw estimation process. Their proposal involves randomly drawing choice sets, estimating parameters, calculating welfare measures, and then repeating this process until the welfare measures stabilize. In some cases, they found that welfare measures for changes in site characteristics did not stabilize even after 100 repetitions.

lakes may form the set of elemental alternatives.⁷ In the random utility model (RUM), individuals are assumed to pick the alternative from their choice set that maximizes their utility. The random utility of elemental alternative j to individual n is:

$$U_{jn} = V_{jn} + \epsilon_{jn}, \quad j=1,\dots,J; \quad n=1,\dots,N \quad (1)$$

where V_{jn} is the portion of the utility function to be estimated and ϵ_{jn} is an error term. Given an error distribution for the ϵ_{jn} 's, the probability that each alternative has the highest utility can be derived. This probability is referred to as the choice probability.

Typically, the ϵ_{jn} are assumed to be independently and identically distributed extreme value random variables with mode 0 and unitary scale parameter. This error structure yields the familiar multinomial logit (MNL) form for each of the $j = 1, \dots, J$ choice probabilities:⁸

$$P_n(j) = \frac{\exp(V_{jn})}{\sum_{k=1}^J \exp(V_{kn})}, \quad (2)$$

where $P_n(j)$ is the probability that individual n chooses elemental alternative j . V_{jk} is commonly written as a linear function of income less travel cost ($Y - C_{jk}$) and the quality characteristics of the sites (X_j):

$$V_{jk} = \mu(Y - C_{jk}) + \beta X_j, \quad j=1,\dots,J; \quad k=1,\dots,K \quad (3)$$

The parameter μ is interpreted as the marginal utility of income and is constant in this specification.⁹ By using (3) in the choice probabilities (2), the preference parameters μ and β

⁷ Peters et al. [1995] compared the results of a RUM using choice sets consisting only of elemental alternatives that anglers were aware of, and a RUM based on a larger set of individual sites. While their research raises many interesting issues regarding anglers' awareness of specific sites, we focus on the effects of defining the choice set using sites in an aggregate versus disaggregate form.

⁸ For ease of exposition, we use a simple multinomial logit form of the RUM. The results discussed can easily be expanded to a nested RUM.

⁹ Morey et al. [1993] discuss specifications relaxing this assumption.

can be estimated by conventional maximum likelihood techniques. To simplify the exposition that follows, we will suppress the n with the understanding that all expressions refer to individuals.

RUMs with Aggregated Sites

As mentioned above, a common way to reduce the size of the choice set is to group elemental alternatives into aggregate alternatives. Here, disjoint sets L_i are formed from the J elemental alternatives, and each of the $i=1, \dots, G$ disjoint sets, L_i , is termed an "aggregate" alternative. When choice probabilities for the elemental alternatives have the MNL form in (2), the random utility of the i -th aggregate alternative can be rewritten as:¹⁰

$$U_i = V_i^* + \ln(M_i) + \ln(Z_i) + \epsilon_i, \quad (4)$$

where V_i^* is the average utility of the i -th aggregate alternative [$V_i^* = (1/M_i) \sum_{j \in L_i} V_j$], M_i is the number of elemental alternatives in the i -th aggregate alternative, and Z_i is a measure of the heterogeneity of the utilities of the elemental alternatives in the i -th aggregate alternative.

The formulation in (4) is useful for examining what happens when aggregate sites are specified and quality is characterized by group averages. Of particular interest is the heterogeneity term:

$$Z_i = \frac{1}{M_i} \sum_{j \in L_i} \exp(V_j - V_i^*) \quad (5)$$

Since Z_i depends on the parameters of V_j , which are unknown at the time of estimation, it cannot be included in the model with aggregate alternatives. In light of this, the commonly estimated aggregate model uses the random utilities for the groups from (4), but excludes the Z_i 's. This results in the following choice probability:

¹⁰ Since the details of this derivation appear in *McFadden*, [1978]; *Ben-Akiva and Lerman*, [1985]; *Train* [1986]; and *Parsons and Needelman* [1992], we do not reproduce them here.

$$P(i)^a = \frac{\exp(V_i^* + \ln M_i)}{\sum_{g=1}^G \exp(V_g^* + \ln M_g)}, \quad (6)$$

where $P(i)^a$ is the probability that an individual chooses the i -th aggregated alternative. Some analyses also omit the $\ln(M_i)$ terms.

Estimating an aggregated model using only V_i^* results in bias unless Z_i and M_i are constant across aggregate alternatives. Because Z_i is unknown, aggregate models may contain some bias even when $\ln(M_i)$ is included. As recognized in the literature, careful definition of aggregate alternatives in terms of the similarity between elemental alternatives in each set and inclusion of $\ln(M_i)$ reduces, but may not eliminate bias [for further discussion see *Ben-Akiva and Lerman*, 1985 or *Parsons and Needelman*, 1992]. Below, we argue that the partial aggregation approach offers an additional way to reduce the heterogeneity of the sites within groups because it can reduce the Z_i 's.

RUMs with Partially Aggregated Sites

In between the aggregated and disaggregated models is the partially aggregated model which utilizes both elemental and aggregated alternatives. Suppose that a set of elemental alternatives, D , are treated as disaggregated sites and the remaining alternatives are aggregated into G' disjoint sets of alternatives. The aggregated alternatives will have utility shown in (3) while the disaggregated alternatives will have utility shown in (4). Treating the disaggregate model as the truth, the correct probability that an individual chooses the i -th disaggregated alternative is:

$$P(j|D) = \frac{\exp(V_j)}{\sum_{j \in D} \exp(V_j) + \sum_{g=1}^{G'} \exp(V_g^* + \ln M_g + \ln Z_g)}, \quad (7)$$

and the correct probability of the i -th aggregated alternative being chosen is:

$$P(i|A) = \frac{\exp(V_i^* + \ln M_i + \ln Z_i)}{\sum_{j \in D} \exp(V_j) + \sum_{g=1}^{G'} \exp(V_g^* + \ln M_g + \ln Z_g)} , \quad (8)$$

where D is the set of disaggregate alternatives and A is the set of aggregate alternatives. With a little algebra, (7) reduces to the MNL probability in (2), and the probability in (8) equals the sum of the MNL probabilities for the sites within the i -th aggregate group. As with the aggregate model in (6), the heterogeneity terms (Z_i) are not known and can not be included when this model is estimated. This causes some bias in the estimated parameters since the aggregated and disaggregated probabilities that can be estimated are:

$$P(j|D)^{pa} = \frac{\exp(V_j)}{\sum_{j \in D} \exp(V_j) + \sum_{g=1}^{G'} \exp(V_g^* + \ln M_g)} , \quad (9)$$

and

$$P(i|A)^{pa} = \frac{\exp(V_i^* + \ln M_i)}{\sum_{j \in D} \exp(V_j) + \sum_{g=1}^{G'} \exp(V_g^* + \ln M_g)} , \quad (10)$$

These expressions reveal the reasoning behind our suggestion to treat popular sites as disaggregate alternatives. In practice, it is not uncommon for an extremely popular recreation site to be in the vicinity of several less popular recreation sites. Moreover, it is generally possible to identify such sites *a priori* by inspecting survey data or by consulting with local experts. In accord with the RUM, these popular sites ought to have high utility. Thus, popular sites are likely to have large measured utilities (V_j 's). Pulling out the sites with high measured utility should reduce the heterogeneity of the sites that remain in aggregate groups. That is, when popular sites are in the set of disaggregate sites, the Z_i 's that remain in (7) and (8) are

smaller and more uniform than those of the fully aggregate model. Reducing the Z_i 's should reduce the potential bias in the parameter estimates based on (9) and (10) where the Z_i 's are omitted. As discussed next, the partially aggregated formulation may also reduce bias in the welfare measures for changes in quality at disaggregated alternatives.

Welfare Measures From These Models

One of the strengths of the RUM is its ability to provide exact welfare measures for changes in site access or changes in site quality. In the completely disaggregated model, the per-trip welfare measure (W) for a change in site qualities is:

$$W = \frac{1}{\mu} \left(\ln \sum_{j=1}^J \exp(V_j^1) - \ln \sum_{j=1}^J \exp(V_j^0) \right), \quad (11)$$

where the 1,0 superscripts denote the site characteristics with and without some policy and j indexes elemental alternatives in the choice set [McFadden, 1981]. If the correct random utilities for the aggregate alternatives could be used (see equation (4)), the welfare measure for the aggregate model would be algebraically equivalent to (11). Of course, with the aggregate model, the Z_i 's are unavailable so that, in practice, the welfare measure for the aggregated model is:

$$W^a = \frac{1}{\mu^a} \left(\ln \sum_{i=1}^G \exp(V_i^{*1} + \ln M_i) - \ln \sum_{i=1}^G \exp(V_i^{*0} + \ln M_i) \right), \quad (12)$$

where i indexes aggregated alternatives. Here, we are defining the welfare measure using the aggregate groups used to estimate the model since this is how the model is likely to be used in practice. Inspecting equation (4) reveals that a change in site quality within the i -th aggregate alternative will affect the average measured utility (V_i^*) and it will also affect the heterogeneity of the alternatives in the group (Z_i). With an aggregate model, only the former effect can be incorporated into the welfare measure (the Z_i 's are by definition unknown). Thus, welfare

measurement with aggregate models will be biased due to an inability to measure all the effects of a quality change (a similar point is made by *Kaoru and Smith*, [1990]).

Comparing the derivatives of W and W^a with respect to the q -th quality variable at the j -th site (X_{jq}) yields some insight into this bias. In the disaggregated model, the derivative is:

$$\frac{\partial W}{\partial X_{jq}} = \frac{\beta_q}{\mu} P(j), \quad (13)$$

where β_q is the estimated parameter associated with X_q and μ is the estimated marginal utility of income, the negative of the travel cost parameter (see (3)). For derivations of this marginal welfare measure see *McFadden*, [1981] or *Hanemann*, [1983]. The expression β_q/μ is often referred to as the implicit price of a change in q . It gives the value of a marginal change in q at all sites. From (13) it is clear that welfare measures from two different models may diverge because the implicit prices differ or because the site probabilities differ. These effects will help us examine differences between welfare measures from aggregate and disaggregate models.

In the aggregated model, the marginal welfare measure for changes in X_q at the j -th site in i -th aggregated alternative is:

$$\frac{\partial W^a}{\partial X_{jq}} = \frac{\beta_q^a}{\mu^a} \frac{P(i)^a}{M_i}, \quad (14)$$

where β_q^a and μ^a are the estimated parameters from the aggregated model. Even if the effect of omitting Z_i was small (so that the estimated parameters are very close), the aggregate model will produce biased welfare measures for individual sites. Comparing (13) and (14) reveals the direction of bias in the welfare measures from aggregated models. If β_q^a/μ^a and β_q/μ are approximately equal, then:

$$\text{sign} \left[\frac{\partial W}{\partial X_{jq}} - \frac{\partial W^a}{\partial X_{jq}} \right] = \text{sign} \left[P(j) - \frac{P(i)^a}{M_i} \right]. \quad (15)$$

Thus, the direction of bias in the site-specific welfare measure that is attributable to aggregation depends on the desirability of the site. This direction of bias is intuitive: sites that are above the group average (e.g., popular sites) will be under valued by the aggregated model since it is likely that $P(j) > P(i)^a/M_j$. The opposite is true for below average (unpopular) sites within a group. *Kaoru and Smith* [1990], and *Parsons and Needelman* [1992] note that parameter estimates from aggregated and disaggregated models are often similar in magnitude, and yet welfare measures can differ substantially. Equation (15) helps to explain these observations.

In the partially aggregated model, the per-trip welfare measure (W^{pa}) for a change in site qualities is:

$$W^{pa} = \frac{1}{\mu^{pa}} \left[\ln \left(\sum_{j \in D} \exp(V_j^1) + \sum_{i=1}^{G'} \exp(V_i^{*1} + \ln M_i) \right) - \ln \left(\sum_{j \in D} \exp(V_j^0) + \sum_{i=1}^{G'} \exp(V_i^{*0} + \ln M_i) \right) \right], \quad (16)$$

where j indexes disaggregated alternatives in set D and $g = 1, \dots, G'$ indexes aggregated alternatives. Again, we are defining the welfare measure using the same aggregate groups used to estimate the model since this is how the model is likely to be used in practice. Just as with the aggregate model, there are heterogeneity terms that get omitted from W^{pa} . Unlike the fully aggregate model, if quality changes at a disaggregate site, then all the relevant changes in welfare can be measured. That is, the marginal welfare measure with respect to a quality variable at the j -th site in a disaggregated alternative resembles the marginal welfare measure from the disaggregated model:

$$\frac{\partial W^{pa}}{\partial X_{jq}} = \frac{\beta_q^{pa}}{\mu^{pa}} P(j|D), \quad (17)$$

where β_q^{pa} (μ^{pa}) are the parameters associated with the q -th quality variable (income) in the partially aggregated model. The reason we suggest including potential policy sites in the set of disaggregate sites is that it will avoid any additional biases due to the "averaging out" of the

welfare effect (the $P(i)/M_i$ versus $P(j)$ effect that exists for sites within aggregate alternatives). For the disaggregated sites, any differences between the marginal measures in the (17) and (13) will be due to differences in the estimated parameters and estimated probabilities, $P(j|D)$ and $P(j)$. Hence, (17) will still contain bias to the extent that the estimated parameters and predicted probabilities differ from those of the disaggregate model (because of the omitted Z_i 's for the grouped alternatives). However, our hypothesis is that by disaggregating the popular and policy sites, the partially aggregated models are likely to be less biased than those of a fully aggregated model. The next section consists of an application that examines the empirical performance of partially aggregated approach.

Application

In this section, we test our hypothesis by estimating some RUMs for sport fishing at lakes in Minnesota. The empirical performance of several partially aggregated RUMs is compared to aggregated and disaggregated models. The parameter estimates and welfare measures from the disaggregated model are treated as the benchmark to which all other specifications are compared. The behavioral data comes from a sport fishing survey conducted in Minnesota. The survey contains information on the angling activities of 1488 individuals over the 1989 calendar year. The sample was randomly drawn from individuals who purchased fishing licenses in the previous year. About 58% of the respondents reported that they had engaged in some type of fishing in 1989, and they took approximately 10 trips during the year. For more information on the survey, see *Estenson* [1990].

Measures of lake quality are derived from physical data collected at individual lakes by the Minnesota Pollution Control Agency and the Minnesota Department of Natural Resources. The data set contains information on 1667 individual lakes which will form our set of elemental

alternatives. The lake quality measures include: lake area, maximum lake depth, the percentage of lake acres that are littoral (near the shoreline), and average secchi disk depth (a measure of water clarity). To avoid correlation with the lake size variable, the littoral acres variable appears as a percentage of lake size. The secchi disk depth variable is averaged over the "open-water season" during a five year period preceding the survey period.¹¹ In each of the estimated models, the natural logarithm of secchi disk depth is used to account for the nonlinear relationship between water clarity and trophic status described by *Heiskary and Wilson* [1990]. Similarly, the natural logarithm of lake acres is used to capture the diminishing effect of lake size described by *Parsons and Kealy* [1992] (i.e., marginal differences in lake size are perceived differently in small lakes than in large lakes).

Because lakes in Minnesota differ from north to south, each of the RUMs is specified as a nested logit with lakes nested by region.¹² The "southern" region is the western and the populous southern portion of the state. Lakes in this region are primarily warm-water lakes that are ideal for bass, bluegill and other warm-water fish species. The "northern" region is the sparsely populated, more pristine portion of the state. The northern region contains cold, clear lakes that are ideal for cool-water fish species such as walleye and northern pike.

Three types of models are estimated: a disaggregated model, an aggregated model, and some partially aggregated models. The disaggregated model treats all 1667 lakes as individual alternatives in the choice set of anglers with each lake being described by its water quality data. The aggregated model treats counties as alternatives (lakes are aggregated to the county level). In this model, each of the 87 counties are described by the average lake data in the county. Four partially aggregated models are estimated using both individual lakes and counties as

¹¹ The Minnesota Department of Natural Resources defines the open-water season as the period from June 24 to September 11 because it corresponds to the maximum productivity and use of Minnesota lakes.

¹² A similar model is described in *Feather et al.*, [1994].

alternatives. Individual lakes are described by their specific quality variables, and aggregated sites are described by averaging the quality measures for the remaining lakes in each county. The four partially aggregated models are estimated with the 25, 48, 103, and 200 most popular lakes¹³ as individual alternatives with remaining lakes aggregated at the county level.

The models were estimated using full information maximum likelihood methods, and the resulting parameter estimates appear in Table 2. The estimated parameters for the travel cost, log area, and inclusive value variables are remarkably similar across all models. The most significant variables, as judged by their t-stats, are the most stable across models. As the level of aggregation decreases, the log secci disk [$\ln(\text{sdm})$], percent littoral acres (plitt), and depth parameters in the partially aggregated models approach those in the disaggregated model. The aggregated model overstates these parameters in magnitude (absolute value) and significance. The parameters for the partially aggregated models generally are closer to the disaggregate model parameters than are those for the aggregate model.¹⁴ The parameter estimates confirm the expected result: as the level of aggregation decreases, the partially aggregated models approach the disaggregated model. Although this is predictable, it is worth noting that the partially aggregated models reasonably approximate the disaggregated model with as much as 94% of the choice set (1564 lakes) aggregated.

To evaluate the models in terms of welfare measurement, the secci disk depth (water clarity) is increased by 25% at the 25 most popular disaggregated sites simultaneously.¹⁵ The

¹³ Popular lakes are defined as those that are visited by numerous individuals. Each of these 25, 48, 103, 200 disaggregated lakes are visited by at least 7, 5, 3, and 2 survey respondents respectively.

¹⁴ The 25 lake partially aggregated model is an exception since it has different signs on the plitt and depth variables, though these parameters are insignificant.

¹⁵ Water clarity, measured by secci disk, is a potential policy variable. Agricultural erosion and fertilizer run-off, as well as pollution from industrial sources is transported to lakes from surface and ground water sources. Policies limiting these pollutants could be evaluated in terms of their impact on water clarity.

mean per-trip compensating variation (CV) estimates appear in Table 3.¹⁶ The top row of Table 3 shows the average over the individuals of their per-trip CV. The bottom row contains the ratio of the average CV for each model divided by the average CV for the disaggregated model. The CV from the aggregated model is about one-third that of the disaggregate model. This result adheres to the aggregation bias in the welfare measure presented in equation (15) which predicts that the aggregate model will under-value popular sites. This direction of bias persists, even though the estimated parameter on clarity for the aggregated model is over four times that of the disaggregated model.

Trends in the welfare measures from the partially aggregated models are similar to those observed in the parameters of these models. As the level of aggregation decreases, the welfare measures approach those from the disaggregated model. When 103 lakes are included in the disaggregated choice set, the ratio of partially aggregated to disaggregated CV is 0.807. When 200 lakes are included, this ratio increases to 0.995.

Welfare changes resulting from increasing sdm by 25% at individual lakes appear in Table 4. The first four rows on Table 4 show changes at the four most popular lakes. The largest CV is associated with Lake Minnetonka, a large lake located in the Twin Cities metro area. Lake Mille Lacs, a prime sport fishing lake located near the Twin Cities, has the next largest CV. Leech Lake, a cold-water lake in the northern section of the state, and Lake of the Woods, a large remote lake bordering Canada, have the smallest CVs of these four lakes. As anticipated, the aggregated model under-values this change in each of the lakes with the

¹⁶ The data used to compute benefit measures from each of these models relies on the same level of aggregation as was used to estimate the respective model. This approach is consistent with *Kaoru et al.* [1995] who argue that analysts who are forced to adopt aggregated models usually do so because they lack disaggregated data.

exception of Lake of the Woods.¹⁷ The aggregated model is somewhat close to the disaggregated model for the most popular lake (Mille Lacs), but off by a large factor for lakes Leech and Minnetonka. The CVs from partially aggregated models follow the usual pattern of approaching those of the disaggregated model as the level of aggregation diminishes.

The next six rows of Table 4 show average welfare changes due to a 25% increase in water clarity at six less popular lakes. Two lakes were randomly chosen from each of the remaining three partially aggregated categories.¹⁸ As lakes become less popular, the aggregated model tends to increasingly over value improvements in water quality. The same trend is evident in the 25 lake partially aggregated model, but disappears in the more disaggregated models.¹⁹ As the level of aggregation diminishes, the CVs from the partially aggregated models approach those of the disaggregated model, but not to the degree that they do when the lakes are more popular (first four rows). However, by a wide margin, the CVs from any of these models are more accurate than the CVs from the aggregated model.

Conclusions

This paper has investigated the use of partially aggregated alternatives (sites) in a random utility model. Partially aggregated models are a compromise between aggregating all sites and not aggregating any sites (disaggregated models). Operationally, the partial aggregation scheme we propose is intuitive and straightforward. First, identify sites which may

¹⁷ Lake of the Woods is the only lake in its respective county. Since none of the aggregated models treat it as part of a group, the results of equation (15) do not apply to this lake. Interestingly, the differences in the welfare measures for Lake of the Woods accord with the usual intuition in that they very closely track the differences in the estimated utility parameter for $\ln(\text{sdm})$.

¹⁸ Independence and North Center lakes are disaggregated alternatives in the 48, 103 and 200 lake models. Artichoke and Cass lakes are disaggregated alternatives in the 103 and 200 lake models. Martin and Fish lakes are disaggregated alternatives in the 200 lake model.

¹⁹ None if these six lakes appear as disaggregated sites in the 25 lake partially aggregated model.

enter any policy analysis. Second, identify the most popular substitute sites. We suggest that popular sites be identified a priori as the sites which receive visits by a large number of individuals.²⁰ Let these two groups of sites appear as disaggregated alternatives in the model. Finally, form similar groups of the remaining sites and aggregate them. Such a model is attractive because it retains the computational and data advantages of a fully aggregated model, but minimizes the disadvantages of aggregate models.

The disadvantage of the aggregation of sites is that it can lead to bias in several ways. (1) Aggregation can lead to bias in the estimated parameters (because the heterogeneity of sites is ignored). (2) Aggregation can lead to bias in the predicted probabilities and/or in the level of the welfare measures (also due to the omission of the heterogeneity of sites). (3) Aggregation means that welfare effects of quality changes at individual sites within a group get "averaged out" because any changes in site heterogeneity cannot be measured. The first effect is widely acknowledged in the literature while the second is implicit in the discussion of *Kaoru and Smith* [1990]. The third effect has not been previously addressed. Specifically, we show that aggregate models will tend to under-value better-than-average sites and over-value worse-than-average sites. This result should help researchers interpret the direction of bias in site-specific welfare measures from models with aggregate sites. We argue that our proposed partial aggregation scheme will reduce each of the three sources of aggregation bias. Our suggestion to disaggregate popular sites is a novel way to reduce the heterogeneity of any remaining

²⁰ An alternative definition of popularity would be the number of visits a site receives. We estimated several partial aggregation models under this definition of popularity and found that the partial aggregation approach did not perform well. When the 100 and 200 most visited sites were disaggregated, the welfare measures from the partial models were three-fourths those of the disaggregate model. A closer look at the data revealed that while some of the sites had a large number of visits, many of those visits were made by a single individual. Recall that if there are some sites that yield high utility relative to other sites in a group, then disaggregating these sites reduces heterogeneity. But for this to work across individuals in the sample, the sites that are disaggregated should yield high utility to most people in the sample, not just a specific person. We believe this is why defining popular sites based on visits made by distinct individuals works better than defining popularity based on overall visits.

aggregate alternatives, and these reductions in the unmeasured heterogeneity of sites ought to reduce the first two sources of aggregation bias. Moreover, our suggestion to disaggregate potential policy sites eliminates the third source of aggregation bias.

The benefits of utilizing a partially aggregated RUM are explored in an empirical application. The application consists of comparing an aggregated, disaggregated and several partially aggregated models. The partially aggregated RUMs yield benefit measures closer to the disaggregated model than those from the aggregated model. As predicted by equation (15), the aggregated model under-values changes in quality at more popular sites. Both the parameter estimates and the welfare measures from the disaggregated and partially aggregated models converge as the level of aggregation decreases. Even at the highest level of aggregation, the partially aggregated model outperforms the aggregated model in terms of producing welfare measures that are closer to those from the disaggregated model. At the lowest level of aggregation, 88% of the lakes are aggregated, and the partially aggregated model produced welfare measures that are close to those produced by the disaggregated model. Since the computational task of estimating RUMs with complex error structures grows with the size of the choice set, these results suggest that substantial reductions in the difficulty of model estimation can be achieved with very modest sacrifices in accuracy.

Table 1 RUMs using some type of Site Aggregation to Define Alternatives

RUMs with some type of site aggregation	Number of alternatives, [†] definition, and level of aggregation
<i>Carson and Hanemann [1987]</i>	29 alternatives with varying degrees of aggregation
<i>Bockstael et al. [1989]</i>	9 alternatives defined at county level with some counties grouped together
<i>Morey et al. [1991]</i>	7 alternatives defined at county level
<i>Jones and Sung [1993]</i>	83 alternatives defined at county level
<i>Morey et al. [1993]</i>	8 alternatives with varying degrees of aggregation
<i>Hausman et al. [1995]</i>	70 to 118 ⁻ alternatives with varying degrees of aggregation
<i>McConnell et al. [1995]</i>	7 alternatives defined at county level with a few counties grouped together
<i>Kling and Thomson [1995]</i>	8 alternatives defined at an aggregate level to match catch rate data
<i>Lin et al. [1996]</i>	4 alternatives defined at an aggregate level to match creel survey areas
[†] Here the number of alternatives refers to the number of spatially distinct alternatives in the model, even though many of these studies estimate nested logit models where different activities can occur within these alternatives (e.g., different fishing modes or species targets) which effectively increases the size of the overall model.	

Table 2 FIML Estimates for the Nested RUMs under Different Levels of Site Aggregation.

Variable ^a	Disaggregated	Fully Aggregated	Partially Aggregated			
			25 lakes	48 lakes	103 lakes	200 lakes
Cost (t-stat)	-0.0685 (-44.1)	-0.0689 (-39.5)	-0.0671 (-40.9)	-0.0686 (-40.7)	-0.0725 (-41.1)	-0.0653 (-43.7)
ln(Area)	0.9035 (51.1)	0.7860 (22.9)	0.8435 (41.7)	0.8414 (43.6)	0.8789 (47.0)	0.8819 (50.6)
ln(Sdm)	0.3385 (5.31)	1.4697 (10.0)	0.8840 (8.27)	0.6792 (6.77)	0.3749 (3.87)	0.4182 (4.82)
Plitt	-0.4379 (-2.61)	-2.6380 (-4.20)	0.2396 (0.84)	-0.2845 (-1.06)	-0.5421 (-2.21)	-0.5617 (-2.69)
Depth	-0.0038 (-2.97)	-0.0442 (-5.31)	0.0010 (0.51)	-0.0011 (-0.65)	-0.0009 (-0.59)	-0.0017 (-1.20)
ln(Size) ^b	N/A	1.0	1.0	1.0	1.0	1.0
Inclusive	0.6063 (13.8)	0.5479 (17.9)	0.5162 (18.1)	0.4933 (18.2)	0.4569 (18.3)	0.6382 (20.0)
Number of sites in the model	1667	87	112	135	190	287
<p>a Cost is the travel and time cost from zip code of origin to center of destination [see <i>Feather et al.</i>, 1995]. ln(Area) is the (average) natural log of lake area in acres for the lakes (counties). ln(Sdm) is the (average) natural log of secci disk depth in meters for the lakes (counties). Plitt is the (average) percent littoral acres for the lakes (counties). Depth is the (average) maximum lake depth in meters for the lakes (counties). ln(size) is the natural logarithm of the number of lakes in each aggregate alternative. Inclusive is the inclusive value.</p> <p>b The parameter on ln(size) is fixed at one to facilitate comparison between each of the models. Allowing the parameter to vary would be akin to allowing the variance of the errors within aggregates to differ from the variance of disaggregate alternatives, i.e., it would be like allowing additional levels of nesting [McFadden 1978]. Constraining the ln(size) parameters isolates the effects of nesting and makes the estimated results directly comparable across models.</p>						

Table 3 Mean CV Estimates for 25% Increase in Clarity (sdm) at the 25 Most Popular Lakes^a

	Disaggregated	Fully Aggregated	Partially Aggregated			
			25 lakes	48 lakes	103 lakes	200 lakes
Mean	0.658	0.228	1.118	0.888	0.531	0.655
Ratio^b	.1	0.347	1.700	1.350	0.807	0.995
<p>a Individual CV's are calculated using the formula for nested models found in Morey (1994).</p> <p>b Ratio of mean to disaggregated mean.</p>						

Table 4 Mean CV Estimates for 25% Increase in Clarity (sdm) at Individual Lakes^a

Lake Name	# Distinct Visitors	Disaggregated	Fully Aggregated	Partially Aggregated			
				25 lakes	48 lakes	103 lakes	200 lakes
Mille Lacs	97	0.1010	0.0531 (0.526)	0.1503 (1.488)	0.1259 (1.247)	0.0757 (0.750)	0.1067 (1.056)
Lake of the Woods	57	0.0075	0.0431 (5.747)	0.0184 (2.453)	0.0138 (1.840)	0.0073 (0.973)	0.0094 (1.253)
Minnetonka	46	0.3417	0.0187 (0.055)	0.5508 (1.612)	0.4978 (1.457)	0.3125 (0.915)	0.3364 (0.984)
Leech	45	0.0365	0.0009 (0.025)	0.0625 (1.712)	0.0444 (1.216)	0.0226 (0.619)	0.0329 (0.901)
Independence	6	0.0030	0.0187 (6.296)	0.0055 (1.855)	0.0026 (0.869)	0.0010 (0.340)	0.0045 (1.501)
North Center	5	0.0009	0.0041 (4.340)	0.0021 (2.245)	0.0006 (0.617)	0.0004 (0.401)	0.0010 (1.053)
Artichoke	3	0.0013	0.0179 (13.984)	0.0110 (8.594)	0.0083 (6.508)	0.0007 (0.544)	0.00159 (1.242)
Cass	3	0.0042	0.0007 (0.177)	0.0002 (0.038)	0.0001 (0.026)	0.0061 (1.453)	0.0063 (1.504)
Martin	2	0.0003	0.0063 (20.720)	0.0030 (9.768)	0.0018 (5.967)	0.0010 (3.234)	0.0004 (1.162)
Fish	2	0.0008	0.0187 (22.241)	0.0055 (6.567)	0.00346 (4.124)	0.0012 (1.395)	0.0014 (1.669)
<p>^a Individual CV's are calculated using the formula for nested models found in Morey (1994). Ratio of disaggregated mean to aggregated/partially aggregated mean appears in parenthesis.</p>							

References

- Ben-Akiva, M. and S.R. Lerman, *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, Cambridge, 1985.
- Bockstael, N.E., K.E. McConnell, and I.E. Strand, Jr., Recreation, in *Measuring the Demand for Environmental Quality*, edited by J.B. Braden and C.D. Kolstad, pp. 227-355, North-Holland, New York, 1991.
- Bockstael, N.E., W.M. Hanemann, and C.L. Kling, Estimating the value of water quality improvements in a recreational demand framework, *Water Resour. Res.*, 23(5), 951-960, 1987.
- Bockstael, N.E., K.E. McConnell, and I.E. Strand, A random utility model for sportfishing: Some preliminary results for Florida, *Mar. Resour. Econ.*, 6, 245-260, 1989.
- Carson, R.T., and W.M. Hanemann, *Southcentral Alaska Sport Fishing Economic Study*, Jones and Stokes Associates, Inc., Report to Alaska Department of Fish and Game, 1987.
- Caulkins, P.P., R.C. Bishop, and N.W. Bouwes, The travel cost model for lake recreation: a comparison of two methods for incorporating site quality and substitution effects, *Am. J. Agric. Econ.*, 68(2), 291-297, 1986.
- Estenson, J., *Survey of the Socioeconomic Aspects of Minnesota Sportfishing*, Minnesota Center for Survey Research Technical Report #90-9. Presented to: C. Anderson, Coldwater Fisheries Research Supervisor, Minnesota Department of Natural Resources, 1990.
- Feather, P.M., D. Hellerstein, and T. Tomasi, "A Discrete-Count Model of Recreational Demand", *J. Environ. Econ. Manage.*, 29, 214-227, 1995.
- Feather, P.M., Sampling and aggregation issues in random utility model estimation, *Am. J. Agric. Econ.*, 76(4), 772-780, 1994.
- Feenberg, D., and E. Mills, *Measuring the Benefits of Water Pollution Abatement*, Academic Press, New York, 1980.
- Hanemann, W.M., A methodological and empirical study of recreation benefits of water quality improvement, Ph.D. dissertation, Harvard University, Cambridge, Mass., 1978.
- Hanemann, W.M., Marginal welfare measures for discrete choice models, *Econ. Lett.*, 13, 129-36, 1983.
- Hausmann, 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," *J. of Public Econ.*, 56, 1-30, 1995.
- Heiskary, S. and C. B. Wilson, *Minnesota Lake Water Quality Assessment Report*, Program Development Section, Division of Water Quality, Minnesota Pollution Control Agency, 1990.
- Jones, C.A., and Y.D. Sung, *Valuation of Environmental Quality at Michigan Recreational Sites: Methodological Issues and Policy Applications*, Final Report, EPA Contract CR-816247-01-2, 1993.
- Kaoru, Y., and V.K. Smith, "Black Mayonnaise' and Marine Recreation: Methodological Issues in Valuing a Cleanup", QE91-02, Resources for the Future, Washington, D.C., 1990.

- Kaoru, Y., Smith, V.K., and J.L. Liu, Using random utility models to estimate the recreational value of estuarine resources, *Amer. J. Agric. Econ.*, 77(1), 141-151, 1995.
- Kling, C.L., and C. Thomson, The implications of model specification for welfare estimation in nested logit models, *Am. J. Agric. Econ.*, 78(1), 103-114, 1996.
- Lin, P.C., R.M. Adams, and R.P. Berrens, Welfare effects of fishery policies: Native american treaty rights and recreational salmon fishing, *J. Agric. Resour. Econ.*, 21(2), 263-276, 1996.
- McConnell, K.E., and N.E. Bockstael, Aggregation in recreation economics: Issues of estimation and benefit measurement, *Northeast. J. Agric. Resour. Econ.*, 13, 181-186, 1984.
- McConnell, K.E., I.E. Strand, and L. Blake-Hedges, Random utility models of recreational fishing: Catching fish using a poisson process, *Mar. Resour. Econ.*, 10(3), 1995.
- McFadden, D., Modeling the choice of residential location, in *Spatial Interaction Theory and Residential Location*, edited by Karlquist et al., North Holland, Amsterdam, 75-96, 1978.
- McFadden, D., Econometric models of probabilistic choice models, in *Structural Analysis of Discrete Data with Applications*, edited by C. Manski and D. McFadden, MIT Press, Cambridge, 1981.
- Morey, E.R., TWO RUMs unCLOAKED: Nested-logit models of site choice and nested-logit models of participation and site choice, in *W-133: Benefits and Costs Transfer in Natural Resource Planning*, Western Regional Publication, Seventh Interim Report, 1994.
- Morey, E.R., and W.D. Shaw, An economic model to assess the impact of acid rain: A characteristics approach to estimating the demand for and benefits from recreational fishing, in *Advances in Applied Microeconomics Vol.5*, edited by Link and V.K. Smith, JAI Press, Greenwich, 1990.
- Morey, E.R., W.D. Shaw, R.D. Rowe, A discrete-choice model of recreational participation, site choice, and activity valuation when complete trip data are not available, *J. Environ. Econ. Manage.*, 20, 181-201, 1991.
- Morey, E.R., R.D. Rowe, and M. Watson, A repeated nested-logit model of atlantic salmon fishing, *Am. J. Agric. Econ.*, 75(3), 578-592, 1993.
- Parsons, G., and M. Needelman, Site aggregation in a random utility model of recreation, *Land Econ.*, 68, 418-433, 1992.
- Parsons, G. and M. Kealy, Randomly drawn opportunity sets in a random utility model of lake recreation, *Land Econ.*, 68, 93-106, 1992.
- Peters, T., W.L. Adamowitz, and P.C. Boxall, Influence of choice set considerations in modeling the benefits from improved water quality, *Water Resour. Res.*, 31(7), 1781-1787, 1995.
- Train, K., *Qualitative Choice Analysis*, MIT Press, Cambridge, 1986.
- U.S. EPA, *Guidelines for Performing Regulatory Impact Analysis*, EPA-230-01-84-003, 1991.
- Waters, S.M., and K.J. Dietz, Measuring the stability of choice set randomization in discrete choice models, working paper, 1996.