WESTERN REGIONAL RESEARCH PUBLICATION

W-133
BENEFITS AND COSTS OF RESOURCES POLICIES AFFECTING PUBLIC AND PRIVATE LAND

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Compiled by
W. Douglass Shaw

Department of Applied Economics and Statistics
Mail Stop 204
University of Nevada
Reno, Nevada 89557-0105

INTRODUCTION

This volume contains the proceedings of the 1999 W-133 Western Regional Project Technical Meeting on "Benefits and Costs of Resource Policies Affecting Public and Private Land." Some papers from W-133 members and friends who could not attend the meeting are also included. The meeting took place February 24th - 26th at the Starr Pass Lodge in Tucson, Arizona. Approximately 50 participants attended the 1999 meeting, are listed on the following page, and came from as far away as Oslo, Norway.

The W-133 regional research project was rechartered in October, 1997. The current project objectives encourage members to address problems associated with: 1.) Benefits and Costs of Agro-environmental Policies; 2.) Benefits Transfer for Groundwater Quality Programs; 3.) Valuing Ecosystem Managment of Forests and Watersheds; and 4.) Valuing Changes in Recreational Access.

Experiment station members at most national land-grant academic institutions constitute the official W-133 project participants. North Dakota State, North Carolina State, and the University of Kentucky proposed joining the group at this year's meeting. W-133's list of academic and other "Friends" has grown, and the Universities of New Mexico and Colorado were particularly well represented at the 1999 W-133 Technical Meeting. The meeting also benefitted from the expertise and participation of scientists from many state and federal agencies including California Fish and Game, the U.S. Department of Agriculture's Economic Research and Forest Services, the U.S. Department of Interior's Fish and Wildlife Service, and the Bureau of Reclamation. In addition, a number of representatives from the nation's top environmental and resource consulting firms attended, some presenting papers at this year's meeting.

This volume is organized around the goals and objectives of the project, but organizing the papers is difficult because of overlapping themes. The last section includes papers that are very important to the methodological work done by W-133 participants, but do not exactly fit one of the objectives. -- I apologize for the lack of consistent pagination in this volume.

On A Personal Note... Any meeting or conference is successful (and fun!) only because of its participants, so I would first like to thank all the people who came and participated in 1999 - listed below. I also want to thank Jerry Fletcher for all his help at this meeting and prior to it, and John Loomis who passed on his knowledge of how to get a meeting like this to work, and who continues to have the funniest little comments to lighten the meetings up. I especially thank Paul Jakus, who helped me to organize this conference and have a lot of fun during it and afterward. Finally, I want to thank Nicki Wieseke for all her help in preparing this volume, and Billye French for administrative support on conference matters.

W. Douglass Shaw, Dept. of Applied Economics & Statistics, University of Nevada, Reno.
June, 1999

P.S. P.F. and J.C. - As far as I can tell, that darn scorpion is still dead!

Investigating Heterogeneity of Preferences in a Repeated Logit Recreation Demand Model Using RP Data*

William S. Breffle and Edward R. Morey

Department of Economics
Campus Box 256
University of Colorado
Boulder, CO 80309-0256
William.Breffle@Colorado.edu
Edward.Morey@Colorado.edu

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Discussion paper
If a more recent version exists it can be found at
http://spot.Colorado.EDU/~morey/index.html

Abstract

Estimating a demand system under the assumption that preferences are homogeneous will lead to biased estimates of individuals' parameters and significantly different expected consumer surplus estimates if preferences are in fact heterogeneous. This paper investigates with revealed preference data several different parametric methods to incorporate heterogeneity in the context of a repeated discrete-choice logit model. The first is the classic method of assuming preference parameters to be functions of individual characteristics. Allowing parameters to vary across individuals as a function of individual characteristics results in preference heterogeneity that persists across choice occasions. Second, a random parameters method is proposed, where preference parameters have some known distribution. Random parameters logit causes the random components to be correlated across choice occasions and, in a sense, eliminates IIA. Finally, two methods are proposed to relax the assumption that the unobserved stochastic component of utility is identically distributed across individuals: the logit scale as a function of individual characteristics and randomization of the logit scale. The randomization of the scale, which is new, allows noise levels to vary across individuals without the added burden of explaining the source using covariates, or the added econometric difficulties with individual-specific scales. Results from an application to Atlantic salmon fishing suggest that imposing homogeneity leads to significantly different expected consumer surplus estimates.

* Thanks to Jose Canals, Nick Flores, Kathleen Rossmann, and Donald Waldman for suggestions that have made this a better paper.

1. Introduction

A common assumption in most consumer demand models is homogeneity of preferences. That is, all individuals are forced to have the same preference parameters in the deterministic portion of utility, and the variance of the random component is assumed to be iid. These strong assumptions will lead to biased parameter estimates on the individual level and significantly different mean consumer surplus estimates if in fact preferences do vary across individuals, which is expected to be the rule rather than the exception.[1]

Several methods are proposed and applied to relax the assumptions of preference homogeneity. Each is discussed separately in the context of a repeated discrete-choice multinomial logit model (MNL) using revealed preference (RP) data,[2] and the advantages and disadvantages are considered. The classic method allows demand parameters to vary as a function of observable socioeconomic characteristics of the individual. Classic models include income-effects models and all other models that make model parameters a function of individual characteristics.

Another technique assumes that preference parameters for all individuals are drawn randomly from some known PDF, although the parameters for any specific individual are unknown. *Random paramters logit (RPL)* is appealing because it allows correlation of random disturbances across choice occasions, and because, in a sense, it eliminates independence of

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[1] Fowkes and Wardman (1988) demonstrate by simulation that the mean of sample-wide parameters, if allowed to vary, may be statistically significantly different from parameters estimated assuming no taste variation, in the presence of nonlinearities.

[2] Morey and Rossmann (1999) have recently examined heterogeneity of preferences using choice experiment data. A *nested* logit model is not used as the basic model because some of the heterogeneous methods can be used instead of nesting to allow for more general substitution patterns without imposing an *a priori* nesting structure. The basic MNL form is used to conduct likelihood ratio tests; otherwise the models would not be comparable on the basis of nested tests.

irrelevant alternatives (IIA). Independent stochastic terms and IIA are two often-criticized assumptions inherent in a logit model. The *nested* logit model was originally introduced to reduce IIA assumptions and to increase the flexibility of the MNL. See, for example, Herriges and Kling (1995), Morey (1999), Morey et al. (1993), Morey et al. (1995), and Shaw and Ozog (1996). However, the nesting structure still imposes restrictions on substitution patterns, while the RPL can allow even more general substitution patterns.

New methods to allow the variances of the random components to vary across individuals or groups are also discussed. While permitting variances to differ across data collection methods is fairly common in the literature (e.g., RP versus stated preference (SP)), there exist very few studies that allow variances to differ across individuals to incorporate heterogeneity. These methods allow some individuals to have "noisier" choice patterns than others, which is empirically indiscernible from *parameter proportionality*, where the demand parameter vector only varies across individuals by a factor of proportionality. A new contribution of this paper is the introduction of a random logit scale parameter, which allows noise levels to vary across individuals without the added burden of having to explain the source of the different levels as a function of individual characteristics that may or may not be correlated with the noise, or the added econometric difficulties associated with trying to estimate individual-specific scales.

The application is a utility-theoretic repeated logit model of Atlantic salmon fishing site choice and participation. Empirical results demonstrate that accommodating heterogeneity significantly improves model performance in each case, and restricting preferences to be homogeneous often leads to significantly different consumer surplus estimates. For models that include socioeconomic characteristics to address heterogeneity, preferences vary as a function of these characteristics in plausible ways.

In Section 2, the techniques are described in detail, along with discussion of relevant existing applications. In Section 3, the methods are applied to the Atlantic salmon recreation demand model, and extensions are proposed throughout. In Section 4, conclusions are presented.

2. Techniques to accommodate preference heterogeneity

Heterogeneity of preferences can be addressed either through the vector of demand parameters (denoted β_i for individual i) or by assumptions about the distribution of the stochastic component of utility (or by using multiple methods simultaneously addressing both components). The first two methods mentioned in the previous section, which allow β_i to vary across individuals either as a function of individual characteristics or randomly based on some distribution, take the former approach.

Other techniques pursue the latter by letting error variances differ across individuals, which may reflect different levels of coherence in decision-making or interest in the activity or the included variables. Allowing the variance of the disturbance term to differ across individuals results in the same likelihood function as allowing the preference parameters to vary across individuals up to a factor of proportionality, because the logit scale parameter and the vector of preference parameters are confounded in estimation.

2.1 A repeated multinomial logit model of recreation demand with homogeneous preferences

Consider a logit model of recreation demand. On each of T choice occasions, the individual chooses from J alternatives the alternative that provides the greatest utility. The utility individual i receives on choice-occasion t if he chooses alternative j is:

$$U_{jti} = V_{ji} + \epsilon_{jti},\ j = 1, 2, \ldots, J. \tag{1}$$

Assume the term V_{ji} is deterministic from both the individual's and the researcher's perspective. It is a linear function of β_i and a vector of explanatory variables x_{ji} associated with angler i and alternative j that are time-invariant, so $V_{ji} = \beta_i' x_{ji}$.[3] The ϵ's vary from period to period and across individuals in a way the researcher cannot observe. Assume ϵ_{jti} is independently drawn from a univariate Extreme Value Distribution with the cumulative distribution function:

$$F(\epsilon_i) = \exp[-e^{-s_i(\epsilon_i)}] \tag{2}$$

where s_i is a positive scale parameter (Morey, 1999). This distribution has $E(\epsilon_i) = (0.57721/s_i)$ and $\sigma^2_{\epsilon i} = \frac{\pi^2}{6s_i^2}$. The probability that individual i will choose alternative j on choice-occasion t is:

$$Prob_{jti} = \frac{e^{s_i V_{ji}}}{\sum_{k=1}^{J} e^{s_i V_{ki}}}. \tag{3}$$

Given these assumptions, the observed trips (y_{ji}) have a multinomial distribution, and the log of the likelihood function for the N recreators is:

[3] The model can easily be generalized to allow time-variant explanatory variables, leading to a more complicated likelihood function than that presented here.

$$\ell = \sum_{i=1}^{N} \sum_{j=1}^{J} y_{ji} \times \ln(Prob_{ji}) \tag{4}$$

Homogeneity of preferences is defined as $\beta_i = \beta$ and $s_i = s \ \forall \ i$. Preference homogeneity implies that the random components are independent and identically distributed, a restrictive assumption which means that the error variances across anglers are assumed to be the same, and also that there is no correlation in random components across choice occasions for a given angler. Homogeneity of preferences also means that choices for a given individual are no more correlated than choices across individuals.

Without loss of generalization, let $s = 1$, the usual assumption in logit models. In Section 3.4, s will be allowed to vary across anglers, introducing heterogeneity in the variance of the stochastic component. It is clear from Equation 3 that allowing to s's to vary across individuals is empirically equivalent to allowing the β's vary up to a factor of proportionality, although the underlying theoretical assumptions are quite different.

2.2 Interacting preference parameters with individual characteristics

This and the following section relax the assumption that $\beta_i = \beta \ \forall \ i,$ while maintaining the assumption that $s_i = 1 \ \forall \ i$. The utility angler i receives from alternative j during choice-occasion t is therefore:

$$U_{jti} = \beta_i{}' x_{ji} + \epsilon_{jti}, \ j = 1,2,\ldots,J. \tag{5}$$

The random component ϵ_{jti} is iid.

The classic and perhaps most straightforward way to allow preferences to vary across individuals is to interact individual socioeconomic characteristics, such as age, gender, or income, with model parameters (Adamowicz et al., 1998). Pollack and Wales (1992) summarize methods of using demand parameters that depend on demographic variables, based on their earlier work and the work of others. Two applications of this technique are Morey (1981) and Morey et al. (1995). The first is a choice-share model of skiing in Colorado, in which individual demand parameters for ski area characteristics are assumed to be functions of skier attributes. The second is a repeated nested logit model of recreational trout fishing in southwestern Montana, where model parameters are interacted with resident status to allow nonresident anglers to have different preferences from residents. In the latter case, forcing nonresidents to have the same preferences would significantly lower economic values for environmental improvements.

Any model that admits income effects also allows for systematic heterogeneity among individuals as a function of their incomes, and there are a multitude of examples. Morey (1999), McFadden (1996), and Herriges and Kling (1997) discuss the theoretical underpinnings of income effects in logit models, and some empirical examples include Morey et al. (1993 and 1998) and Buchanan et al. (1998). Models with income effects are not investigated here. Also, a new literature is emerging that includes latent constructs and psychometric measures based on individual attitudes and perceptions in addition to demographic factors in discrete choice models. McFadden (1986) initiated work in this area to develop market forecasts. See Boxall and Adamowicz (1998) for an application to explain wilderness park choice, and also Ben-Akiva et al. (1997).

Note that allowing β_i to vary across individuals as a function of individual characteristics results in preference heterogeneity that persists across choice occasions. For example, suppose that the catch parameter in a fishing model is increasing in skill level. An individual with high skill will have a higher than average catch parameter in each of the choice occasions. As a result, the deterministic component of utility, V_{ijt}, is correlated across choice occasions.

One reason that an application of this well-known method is included in this paper is because it is useful to compare the assumptions and results to other heterogeneous models, and because a complete treatment of heterogeneous preferences is incomplete without it. The main advantage of this technique is to allow β_i to vary across individuals in a systematic way as a function of individual characteristics. The researcher can predict how different types of individuals are affected by different policies, and consequently reach conclusions about distributional impacts.[4] The primary drawback is that β_i may not in fact vary as a function of observable individual characteristics, and model results are expected to be sensitive to the way in which the parameters and data are allowed to interact.

2.3 Random parameters logit

Another way to incorporate heterogeneity through β is to assume that one or more parameters in the vector is drawn from a known distribution, although the unique values of the parameters for a given individual in the sample cannot be known. RPL is a special case of *mixed logit* because the probability of observing an individual's sequence of choices is a mixture of logits with a prespecified mixing distribution (Revelt and Train, 1997).

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[4] Benefits can vary widely as a function of individual type. See, for example, Morey et al. (1998).

Two recreational site choice examples using RPL with revealed preference data are a partial demand system of fishing site choice in Montana (Train, 1998) and a complete demand system of participation and site choice in the Wisconsin Great Lakes region (Phaneuf et al., 1998). Our random parameters model, unlike Phaneuf et al., addresses preferences for unobserved characteristics. Both of these studies find that randomizing parameters significantly improves model fit and significantly affects consumer surplus estimates for changes in environmental quality. RPL has also been applied to choice experiments (conjoint analysis) to model demand for a wide array of commodities and environmental amenities, including alternative-fuel vehicles (Brownstone and Train, 1996); appliance efficiency (Revelt and Train, 1997); forest loss along the Colorado Front Range resulting from global climate change (Layton and Brown, 1998); and the level of preservation of marble monuments in Washington, DC (Morey and Rossmann, 1999).

RPL addresses heterogeneity across the population without having to confront the sources of individual heterogeneity, which is both its strength and weakness. As noted by Adamowicz et al. (1998), RPL provides more flexibility in estimating mean utility levels but little interpretability in terms of distributional impacts associated with heterogeneity.

Like interaction, the RPL model specification assumes the β_i's vary across anglers rather than being restricted to be the same as assumed in Section 2.1. The coefficient vector for each individual is expressed as the sum of two components, the population mean vector (b) and an individual vector of deviations (υ_i): $\beta_i = b + \upsilon_i$. By assuming that υ_i is constant over choice-occasions for each individual, the unobserved components of utility become correlated. By allowing for preference heterogeneity in this fashion, the restriction of independence associated with the nonrandom logit model is removed (Phaneuf et al., 1998). Train (1998) expects such persistence in the unobserved factors that affect utility over time and over sites.

If we knew each angler's preferences, the β_i's, the probability of observing angler i's choices over the season would be:

$$P_i = \prod_{j=1}^{J} \left[\frac{e^{\beta_i' x_{ji}}}{\sum_{k=1}^{J} e^{\beta_i' x_{ki}}} \right]^{y_{ji}}. \tag{6}$$

However, the individual deviation υ_i is unobservable. Only the PDF $f(\beta)$ is assumed to be known, so the joint probability of observing angler i's choices conditioned on υ is the integral of Equation 3 over β:

$$P_i = \int_{-\infty}^{\infty} \prod_{j=1}^{J} \left[\frac{e^{\beta' x_{ji}}}{\sum_{k=1}^{J} e^{\beta' x_{ki}}} \right]^{y_{ji}} f(\beta|\theta) d\beta \tag{7}$$

where θ represents the parameters of the distribution of β. V_{ji} is no longer deterministic, but is now a random variable. Analytical evaluation of this integral is generally not possible, but advances in computer simulations allow for easy approximation based on a large number of random draws, R, from $f(\beta)$ using a pseudo-random number generator:[5]

$$SP_i = \frac{1}{R} \sum_{r=1}^{R} \prod_{j=1}^{J} \left[\frac{e^{\beta_r' x_{ji}}}{\sum_{k=1}^{J} e^{\beta_r' x_{ki}}} \right]^{y_{ji}}, \tag{8}$$

[5] If only a small number of elements of β are randomized, other techniques to evaluate the integral such as Gaussian quadrature may be used to increase speed and accuracy (Abramowitz and Stegun, 1965). See Stern (1998) for a discussion of simulated ML and its advantages.

where β_r is a single draw from $f(\beta)$, and SP_i is the simulated probability of observing the individual's choices. The simulated log-likelihood function for the RPL is therefore:

$$s\ell = \sum_{i=1}^{N} \ln(SP_i) \tag{9}$$

Nonrandom logit has the property that the ratio of probabilities of visiting two sites is unaffected by the inclusion of or change in a third site. RPL does not have this property due to the correlation in unobserved utility across choice occasions and alternatives resulting from persistent preference heterogeneity incorporated randomly, rather than deterministically as in the previous section. [6] The absence of this property is clear by examining the ratio of probabilities of visiting sites j and j' on the t-th choice occasion (conditioned on the PDF of β, but unconditional on alternatives chosen on other choice occasions):

$$\frac{\displaystyle\int_{-\infty}^{\infty} \frac{e^{\beta' x_{ji}}}{\sum_{k=1}^{J} e^{\beta' x_{ki}}} f(\beta|\theta) d\beta}{\displaystyle\int_{-\infty}^{\infty} \frac{e^{\beta' x_{j'i}}}{\sum_{k=1}^{J} e^{\beta' x_{ki}}} f(\beta|\theta) d\beta} \tag{10}$$

In a nonrandom logit model, the denominators cancel out, leaving the ratio as a function only of the characteristics of j and j'. In the RPL, the denominators do not cancel out of the integrands because they also contain υ.

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[6] Hausman and Wise (1978) were the first to incorporate correlation across choice occasions in the context of a random probit model. Heterogeneity of preferences was addressed by allowing correlation among the random components of utility across alternatives. At the time, simulation methods were not available, so they were limited to three alternatives because their probit model integrates over utility differences between alternatives rather than parameter distributions as in the RPL.

If IIA means that the ratio of probabilities of visiting two sites is unaffected by changes in a third site, then RPL eliminates IIA. This interpretation is shared by Brownstone and Train (1996), Train (1997), Revelt and Train (1997), and Phaneuf et al. (1998). However, even with random parameters, how an individual ranks any two alternatives is independent of the existence or characteristics of any other alternative. Remember that β_i is not a random variable from the individual's perspective. In this sense, how the individual ranks alternatives is independent of irrelevant alternatives.

2.4 *Heterogeneity of the stochastic component*

The interaction and RPL methods address heterogeneous preferences by allowing β in the conditional indirect utility functions to vary across the population. Another strategy is to allow for heterogeneity in the stochastic components, the ϵ's. Although it is assumed that all individuals have the same β's, and therefore *expected* behavior of two individuals with the same characteristics would be identical, the assumption that each individual's ϵ's are drawn from the same distribution is relaxed. The assumption that the ϵ's are independent across choice occasions is retained, but different individuals can have different error variances ($\sigma_{\epsilon i}^2$). As a result, different individuals with the same characteristics are allowed to have different levels of noise in their decision-making (for example, see Johnson and Desvouges (1997)).

As discussed in Section 2.1, it is typical to assume that all individuals have stochastic components drawn from the same distribution. Under this assumption, all of the individual scale parameters, the s_i's in Equation 3, are the same and usually normalized to one without loss of generality. To allow for heterogeneity in the stochastic component, this restriction is relaxed, and individual- or group-specific s's are estimated separately, or s can be randomized as in the RPL, the latter being a completely new method proposed in this paper. One scale must be normalized (to one or some other value) to achieve identification in the model. As emphasized above, allowing s to be heterogeneous is empirically indistinguishable from parameter proportionality (Louviere, 1996); that is, all β_i's are scaled up or down proportionately across individuals, as shown in Equation 3. In that sense, the methods in this section are more restrictive than either RPL or interaction. While heterogeneous scales require parameters to vary only up to a factor of proportionality across individuals, the other methods allow more general variation.[7] Note that s_i is inversely proportional to $\sigma_{\epsilon i}^2$. Therefore, an individual with a small (large) amount of noise in the decision process will have a relatively large (small) s_i, and the model will predict the individual's choices relatively well (poorly).

Several studies allow for differing levels of noise in different data sets or resulting from different data-generating processes, rather than to admit unobserved heterogeneity across individuals.[8] Incorporating heterogeneity of preferences through s is a much different exercise with a groundbreaking goal, and which also presents new challenges. For example, when merging k datasets, only k - 1 scale parameters need to be estimated, where k is some small integer; preference heterogeneity may require that a different s_i be estimated for every individual, or subsets of individuals where grouping is nonrandom and based on logic or some expectation.

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[7] Note that when there is only one slope parameter, allowing s or β to vary is equivalent because s and β cannot be separated in estimation.

[8] For example, Swait and Louviere (1993) propose a test for multinomial logit parameter comparisons using identical utility specifications but different data sources. Louviere and Swait (1997) propose a nonparameteric approach for estimating scale parameters when different data sets are aggregated. Swait et al. (1994) use scaling to explain differences in the magnitudes of unexplained variance between SP and RP data from the same respondents in a model of freighter shipping choice under the assumption that the SP data reflects tradeoffs more robustly and therefore contains less noise. Ben-Akiva and Morikawa (1990) also examine the differences between RP and SP data-generating processes using scales.

Alternatively, the new random scale method is an appealing way to circumvent the problems associated with estimating a huge number of individual-specific s's. First, it may be difficult or impossible to estimate a different $\hat{s}_i$ and its standard error for each individual in the sample. RP data sets may have many corner solutions and limited variability across the data, and attempting to estimate individual-specific parameters may be asking too much. A finite ML estimator of s, a prerequisite for consistency, may not exist for those who make purely random choices, or for those whose choices are completely explained by β, because the likelihood function may be continuously increasing as $s_i \to 0$ or $s_i \to \infty$ (Morey and Rossmann, 1999). Second, even if individual scales could be estimated for everybody, they would provide no information on why a given individual's error variance is high or low. Using a random scale parameter in a similar way as the random preference parameters in the RPL allows for heterogeneity across individuals in the variance of the stochastic term, but it requires estimating only enough parameters to characterize the distribution of the scales (e.g., two for the lognormal distribution) rather than n - 1 different individual-specific scale parameters. Further, the random scale does not require estimation of the scale parameter as a function of individual covariates, the specification of which may lead to specification bias.

2.5 *Individual-specific preference parameters*

It is possible in theory to estimate individual-specific models, in which no parameters are shared, if the quantity of data is sufficient and the data exhibit enough variation. Usually the data do not allow identification or estimation of all of the parameters at the individual level. Successful estimation of individual-specific models is most likely using choice-experiment data, with many observations per individual that exceed the number of parameters to estimate.[9] Individual-specific recreation demand models using RP data would be difficult to estimate because of the typical lack of variation in choices and a small number of trips taken by many individuals, which could be avoided by the careful design of a choice-experiment survey (for discussion, see Morey and Rossmann (1999)).

A consistent estimator of slope parameters in models with some individual-specific parameters and some shared parameters does not exist. Chamberlain (1984) demonstrates that a unique feature of the logit formulation is the ability to estimate individual fixed-effect constants without introducing inconsistency in the other shared parameters. This result does not extend to slope parameters, so interaction and RPL are the best alternatives to individual-specific β_i's to admit heterogeneity in V_{ji}.

3. Repeated logit models of Atlantic salmon fishing participation and site choice that allow heterogeneity

The empirical application is a repeated nested logit recreation demand model of Atlantic salmon fishing participation and site choice. The model is utility-theoretic and complete. Each of the techniques is applied to the model, and expected compensating variations are estimated for changes in site characteristics. The basic model assuming homogeneous preferences is developed

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[9] For examples, see Johnson and Desvousges (1997); Beggs, Cardell, and Hausman (1981); and Morey and Rossmann (1999). Estimating a large number of individual-specific coefficients is always a daunting task. For example, about one-fourth of the individuals are nonconvergent in the first study, and about half have undetermined coefficients in the second study.

and estimated in Section 3.1. The techniques to add heterogeneous preferences are discussed and applied in Sections 3.2 through 3.4, along with comparisons to the basic model.

3.1 Model 1: A logit model of Atlantic salmon fishing with homogeneous preferences

During a fishing season, an Atlantic salmon angler has a finite number of choice occasions, assumed to be 100,[10] to allocate to nine alternatives, including five salmon river groups in Maine (Penobscot, Machias group, Dennys, Kennebec group, and Saco), three salmon river groups in Canada (Nova Scotia rivers, New Brunswick rivers, and Quebec rivers), and a nonparticipation alternative that allows substitution in and out of fishing.

The data used to fit the logit model are from a sample of 145 Maine anglers who held Atlantic salmon fishing licenses in 1988 and were active at these sites. The data set includes complete trip records on the number of visits each angler took to each of the eight Atlantic salmon fishing areas (y_{ji}). The average angler took about 20 trips to these sites and 14 to the Penobscot River in Maine alone. The data also include exogenous expected catch rates, angler incomes, and fishing costs, the p_{ji}'s, which vary widely across anglers and sites. Trip costs comprise transportation costs, on-site costs such as guides and lodging, and the opportunity cost of time, including fishing, travel, and additional on-site time (e.g., waiting time, overnight time). Finally, the data set includes socioeconomic characteristics for each angler, including age, years of fishing experience, and whether the angler belongs to a Penobscot fishing club. This particular data set was first used to estimate a nested logit model of participation and site choice with income effects in Morey et al. (1992).

[10] Over 97% of sample anglers took 100 or fewer trips during the season.

The deterministic portion of angler i's conditional indirect utility function for fishing at site j, V_{ji}, is a function of a constant (α_0), a dummy (D_j) that equals one if the site is in Canada, the budget per choice occasion (B_i), the trip cost to visit site j (p_{ji}), and the site-specific expected catch rate: $V_{ji} = \alpha_0 + \alpha_{0C}D_j + \beta_0(B_i - p_{ji}) + \alpha_1(1 - D_j)(catch_j) + \alpha_1(\alpha_{1C}D_j)(catch_j), j = 1, 2, ..., 8$. The expected catch rates at the Canadian sites are considerably higher than at the Maine sites. To account for this difference, the catch parameter is a step function constructed by multiplying the catch parameter (α_1) by a catch-scale parameter (α_{1C}) if the site is in Canada. The price parameter, β_0, is interpreted as the marginal utility of money. The conditional indirect for nonparticipation, V_{9i}, is a function of a constant, the budget per-choice occasion spent on the numeraire if fishing is not chosen, and socioeconomic characteristics of the angler: $V_{9i} = \alpha_{09} + \beta_0(B_i) + \alpha_2 age_i + \alpha_3 yrs_i + \alpha_4 club_i$, where *age* is the angler's age, *yrs* is years of fishing experience, and *club* equals one if the angler is a member of the Penobscot fishing club.[11] This is a no-income-effects model; the choice-occasion probabilities are not a function of the budget.

The ML algorithm (version 4.0.18) in Gauss (Aptech Systems, 1996) was used to find the estimates of the parameters that maximize the likelihood of observing the sample trip records, given exogenous trip costs, expected catch rates, and angler characteristics. The parameters are all significant and are reported in Table 1. The estimated parameters indicate that site visitation increases in expected catch and is a decreasing function of trip cost. The catch step function shows that increases in catch are more important when catch is lower (the Maine sites) than when

[11] The three constants α_0, α_{0C}, α_{09} were included to account for the effects of any unobserved variables in the participation decision and the choice of region. The model was identified by setting α_0 equal to zero. Note that because the conditional indirect for nonparticipation is a function of angler characteristics, Model 1 does allow preferences to be heterogeneous in the classic sense to some degree in terms of the participation decision of how much to fish, although the model is called "homogeneous". Modeling participation as a function of demographic variables is common in the recreation demand literature, so this does not represent a new contribution.

Table 1
Parameter Estimates[1]

Parameters	Model 1 Homogeneity	Model 2 Interaction	Model 3 RPL	Model 4 Group scales	Model 5 Random Scale
Fishing parameters[2]					
α_{0C}	4.409 (7.95)	5.124 (13.88)	2.971 (1.87)[6]	3.969 (7.46)	3.993 (7.48)
β_0	-0.0157 (-43.00)	-0.0154 (-42.61)	-0.0175 (-38.34)	-0.0144 (-29.99)	-0.0147 (-30.32)
α_1	15.834 (15.00)	32.363 (9.46)	39.220 (8.21)	14.808 (13.95)	12.466 (11.57)
α_{1C}	0.0620 (4.65)	0.0377 (5.87)	0.133 (1.45)	0.0630 (4.68)	0.0743 (4.51)
Particip. parameters[3]					
α_{09}	2.296 (17.93)	3.726 (11.89)	4.517 (6.03)	2.304 (18.47)	2.322 (18.10)
α_2	0.0200 (12.08)	-0.0121 (-1.87)	-0.0240 (-1.49)	0.0167 (8.94)	0.0218 (11.68)
α_3	-0.121 (-18.09)	-0.152 (-6.04)	-0.0577 (-1.09)	-0.100 (-12.10)	-0.134 (-15.60)
α_4	-0.647 (-13.52)	0.386 (2.14)	-0.404 (-1.01)	-0.868 (-12.80)	-1.0025 (-13.80)
Hetero. parameters					
γ_1 for age		-0.373 (-5.22)	-0.613 (-5.41)		
γ_2 for yrs		-0.437 (-1.55)	1.210 (2.76)		
γ_3 for club		12.314 (6.16)	6.158 (2.14)		
σ_{0C}			6.653 (9.50)[6]		
σ_{09}			1.995 (14.84)[6]		
group scales[4]				1.0 (fixed), 1.270 (20.05), 0.945 (28.33), 1.236 (18.70), 1.087 (28.56), 1.211 (21.53), 1.034 (28.82), 1.117 (25.14)	
σ_{is}[5]					0.642 (16.15)
Lik. ratio stat. [d.o.f.]	NA	67.96 [3]	4054.20 [5]	47.30 [7]	1956.95 [1]

1 Asymptotic t-statistics in parentheses.

2 Fishing : $V_{ji} = \alpha_0 + \alpha_{0C}Dj + \beta_0(B_i - p_{ji}) + \alpha_1(1 - D_j)(catch_j) + \alpha_1(\alpha_{1C}Dj)(catch_j), j = 1, 2, ..., 8$; α_0 fixed at zero for identification in all models.

3 Participation: $V_{9i} = \alpha_{09} + \beta_0(B_i) + \alpha_2 age_i + \alpha_3 yrs_i + \alpha_4 club_i$.

4 Group 1: young, inexperienced, no club; Group 2: young, inexperienced, club; Group 3: young, experienced, no club; Group 4: young, experienced, club; Group 5: old, inexperienced, no club; Group 6: old, inexperienced, club; Group 7: old, experienced, no club; Group 8: old, experienced, club.

5 σ_{is} is the standard deviation of ln(s) in Model 5 where s is the random scale. The mean of ln(s) is fixed at zero for identification.

6 α_{0C} (α_{09}) is the mean and σ_{0C} (σ_{09}) is the standard deviation of the normal distributions of the Canadian (nonparticipation) contant in Model 3.

catch is high (the Canadian sites). Socioeconomic characteristics such as age, years of fishing experience, and club membership are all important in the participation decision of how often to fish. Older anglers tend to fish less, and those with more years of experience or belonging to a fishing club tend to fish more.

The Penobscot River in Maine is a very popular fishing site with relatively high catch for a Maine site. Expected compensating variations, E(*CV*)s, are estimated for three environmental changes at the Penobscot for all models: doubling the catch rate, halving the catch rate, and elimination of the site entirely. Both improvement and deterioration experiments are conducted because million-dollar fish stocking policies to improve the catch rate and dam projects for hydroelectric power (which would lower the catch rate) are relevant to the Penobscot. The E(*CV*) per choice-occasion for angler *i* for a logit model with no income effects is simply calculated as:

$$E(CV_i) = (1/\beta_0)\times[V_i^0 - V_i^1], \qquad \textbf{(11)}$$

where $V_i = \ln(\sum_{j=1}^{9} \exp(V_{ji}))$, the expected utility per choice occasion, and the superscripts denote conditions before and after the change (Morey, 1999). The total seasonal E(*CV*) is the choice-occasion E(*CV*) multiplied by 100. Seasonal E(*CV*)s and confidence intervals for the mean E(*CV*)s simulated using 500 pseudo-random draws based on the estimated covariance matrix of the parameters are presented for Model 1 in Table 2. The mean seasonal E(*CV*) for doubling the catch, for example, is $2,270, which is consistent with the very avid, serious nature of these recreational anglers who pay high trip costs to go fishing (often in the hundreds or thousands of dollars), and receive high benefits from the activity.

Table 2 Expected Seasonal Compensating Variations for Three Penobscot Scenarios[1]					
E(*CV*)s	Model 1 Homogeneity	Model 2 Interaction	Model 3 RPL	Model 4 Group Scales	Model 5 Random Scale
Double catch					
mean	\$2270	\$2978[2]	\$3514[3]	\$2300	\$3140
conf. interval	\$1707 to \$2833	\$2345 to \$3301	\$2720 to \$4308	\$1606 to \$2994	\$1976 to \$4304
median	\$2081	\$1489	\$2104	\$2102	\$2748
minimum	\$4	-\$68	-\$26	\$6	\$1
maximum	\$6859	\$17305	\$20561	\$7421	\$10115
Halve catch					
mean	-\$470	-\$521	-\$743[3]	-\$475	-\$164[3]
conf. interval	-\$537 to -\$403	-\$590 to -\$452	-\$908 to -\$578	-\$557 to -\$393	-\$213 to -\$115
median	-\$346	-\$220	-\$391	-\$361	-\$92
minimum	-\$1960	-\$3711	-\$4931	-\$2030	-\$1446
maximum	\$0	\$36	\$13	-\$1	\$0
Eliminate site					
mean	-\$908	-\$939	-\$1312[3]	-\$911	-\$582[3]
conf. interval	-\$965 to -\$851	-\$996 to -\$882	-\$1579 to -\$1045	-\$989 to -\$833	-\$653 to -\$511
median	-\$638	-\$627	-\$900	-\$681	-\$230
minimum	-\$4129	-\$5074	-\$6704	-\$3882	-\$1789
maximum	-\$1	-\$1	-\$1	-\$2	-\$1

1 Confidence intervals for the mean E(*CV*)s were simulated using the estimated covariance matrix.
2 Statistically significantly different from the Model 1 mean at a 10% level of significance.
3 Statistically significantly different from the Model 1 mean at a 5% level of significance.

3.2 *Model 2: A logit model with the catch parameter as a function of angler characteristics*

In Model 1, only the participation decision is a function of angler characteristics. In this section, the model is generalized by making the site-choice decision also a function of angler characteristics. The catch parameter is interacted with age, years of experience, and the club dummy. The variables are interacted linearly, so the conditional indirects for the fishing alternatives become: $V_{ji} = \alpha_0 + \alpha_{0C}D_j + \beta_0(B_j - p_{ji}) + \alpha_1(1 - D_j)(catch_j) + \alpha_1(\alpha_{1C}D_j)(catch_j) + \gamma_1(1 - D_j)(age_i)(catch_j) + \gamma_2(1 - D_j)(yrs_i)(catch_j) + \gamma_3(1 - D_j)(club_i)(catch_j) + \gamma_1(\alpha_{1C}D_j)(age_i)(catch_j) + \gamma_2(\alpha_{1C}D_j)(yrs_i)(catch_j) + \gamma_3(\alpha_{1C}D_j)(club_i)(catch_j), j = 1, 2, ..., 8$.

Parameter estimates reported in Table 1 indicate members of a fishing club are more concerned with catch, and older anglers are less concerned. Perhaps fishing club members are more interested in the sporting aspect of fishing, and older anglers are more interested in fishing for the pure enjoyment of the activity, regardless of what they catch. Years of fishing experience is not a significant determinant of the catch parameter in Model 2. Two individuals in the sample who are older and are not club members have negative catch parameters, and thus negative E(*CV*)s for catch improvements. Negative catch parameters may simply be an artifact of the model specification. Alternatively, some individuals may in fact have negative catch parameters if omitted variables are correlated with catch. For example, a larger catch rate is expected to be correlated with higher visitation and possibly more congestion at a given site. Perhaps these anglers have a strong preference for isolated sites with few visitors, even if it means catching fewer fish.

A likelihood ratio test shows that Model 2 is statistically superior to Model 1; incorporating heterogeneity matters. Further, although older anglers who are not club members have E(*CV*)s for catch improvements in the interactive model that are lower than in Model 1, the mean E(*CV*)s for the sample as a whole, reported in Table 2, are somewhat larger in absolute value from Model 2 for all Penobscot scenarios, although the medians are smaller. Club members tend to have the highest E(*CV*)s. Perhaps the most important finding is that the range of E(*CV*)s over the sample is much larger in Model 2. Incorporating heterogeneity by making the catch parameter a function of socioeconomic characteristics not only allows the researcher to determine which groups are most affected by environmental changes, but also allows a much wider range of behavior of and estimated impacts on different types of anglers.

3.3 Model 3: A RPL model with interaction

Model 3 is a RPL model that is an extension of Model 2, and therefore uses two heterogeneous methods; heterogeneity of the catch parameter is again accomplished using the same interactions as in the previous section. The constants α_{0C} and α_{09} (the Canadian and nonparticipation constants, respectively) are natural candidates to be random parameters because they represent the effects of all other relevant variables on the participation decision and regional choice (α_0 for Maine is still fixed for identification of the model). It is likely different anglers respond to unobserved variables differently, but the way specific individuals respond is by definition unobservable. Therefore, it is assumed that these constants vary across anglers randomly. They are drawn from normal distributions with means α_{0C} and α_{09} and standard deviations σ_{0C} and σ_{09}, which are estimated in the model. A normal distribution was used for both constants because there are no restrictions on the signs, and because the proportion of possible values decreases for value ranges farther from the mean.[12]

Note that Model 3 allows for systematic variation in the catch parameter because it is reasonably explained in terms of socioeconomic characteristics. It may be more informative for the researcher to be able to explain why parameters differ across individuals in a systematic fashion where possible, as in Model 2 (and again in Model 3) where interaction of the catch parameter with angler characteristics is statistically significant. Therefore, only the constants are randomized in Model 3 with unobserved variables.

A comment is warranted about the choice of the number of repetitions, R, an issue that is not examined extensively in the literature. The simulator is unbiased with only one draw of β.

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[12] Distributional assumptions are simply approximations of the true distributions, which are unknown. The normal and lognormal are typically used, the latter to impose restrictions on a parameter's sign. Train (1998) uses a lognormal distribution for the parameter on fish stock to constrain it to be positive (i.e., all anglers are assumed to gain utility from catching fish), but Phaneuf et al. (1998) use a normal distribution. Train (1998) also allows the price parameter to be random and lognormally distributed. Layton and Brown (1998), however, warn of undesirable effects on the distribution of the E(CV)s as a result (because the price parameter is in the denominator of the CV formula), and hold the price parameter fixed. Phaneuf et al. (1998) also hold the marginal utility of money fixed. RPL results may be sensitive to the distributional assumptions. For example, in the Atlantic salmon model, both normal and lognormal distributions for the catch parameter were investigated in preliminary analyses. E(CV)s were found to be highly sensitive to the standard deviation of the catch parameter, especially in the lognormal case. The long right tail combined with the nonlinearity of the E(CV) calculation led to unrealistically enormous economic values.

However, increasing the number of repetitions increases the accuracy of the simulator and reduces *simulation noise* (Layton and Brown, 1998).

The number of draws should be large enough so that the model parameters and E(*CV*)s are insensitive to different random number draws. A total of 2,500 draws was used in the integration simulators in this paper. With this large number, most model parameters did not vary at two or three significant digits. Perhaps more importantly, mean E(*CV*)s changed by less than 1%, whereas with only 100 draws they changed by more than 10%. Note that this number of draws is considerably larger than the numbers reported in other studies, which range from 250 to 1,000, although one can expect the appropriate number to vary with the study.[13]

Model 3 is statistically superior to both Models 1 and 2 on the basis of likelihood ratio tests, and in addition, σ_{0C} and σ_{09} have highly significant asymptotic t statistics. The parameter estimates for the RPL are reported in Table 1.[14] The values of α_{0C} and σ_{0C} are 2.97 and 6.65, and the values of α_{09} and σ_{09} are 4.52 and 2.00. The ratios of the standard deviation to the mean are 2.24 and 0.44, which match well with the ratios for random parameters in other studies valuing environmental improvements. The range over 20 parameters in 3 studies is 0.40 to 14.29, with a mean of 2.28 and a median of 1.43 (Train (1998), Phaneuf et al. (1998), and Layton and Brown (1998)).

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[13] Brownstone and Train (1996) examine the sensitivity of average probabilities, the log-likelihood function, and parameter gradients to different numbers of draws and different sets of random numbers (i.e., different values for the random number generator seed), but hold the estimated parameters constant as they conduct the tests (i.e., a new model is not estimated for every value of the seed).

[14] In estimation of RPL models, it was found that scaling the parameters was critical to obtain convergence. Parameters should be scaled so that the diagonal elements of the Hessian are roughly the same order of magnitude. Note that the RPL software developed by Kenneth Train was not used to estimate Model 3. In this study, site characteristics do not vary over choice occasions, so the coding of the likelihood function was simpler than that coded by Train. Programs are available from the first author upon request.

For a RPL model, the E(CV) per choice occasion for angler i is obtained by simulating integration of Equation 11 over the PDF of β:

$$E(CV_i) = \frac{1}{R} \sum_{r=1}^{R} (1/\beta_0) \times [V_{ri}^0 - V_{ri}^1], \qquad \textbf{(12)}$$

Because seasonal E(CV)s are additive and each component can be integrated separately, the seasonal E(CV) can be computed as the simulated E(CV) per choice occasion multiplied by the number of choice occasions. The mean and median seasonal E(CV)s from the RPL in Table 2 are statistically significantly higher for all scenarios than for either Models 1 or 2, indicating that randomization has a significant impact on economic values. The ranges on E(CV)s are also wider.

Removal of IIA assumptions in terms of probabilities is a desirable property of RPL. Making the regional constants random removes IIA between Maine and Canada, but not within a region. As an example, the percent changes in the probabilities of visiting each of the eight fishing sites on the t-th choice occasion (independent of what occurs on other choice occasions) when the catch rate at the Penobscot doubles are computed. The RPL and nonrandom Model 1 are compared using a representative angler.[15]

The nonrandom model predicts the angler's probabilities of visitation to all other sites on the t-th choice occasion when the Penobscot catch doubles will decrease by the same amount (60%), as a result of IIA. The probability of visitation to the Penobscot will increase by 155%. The particular randomization of the constants in Model 3 results in a feature similar to that of a nested logit model. When the Penobscot catch doubles, the probability of visiting any of the other

[15] For this example, the angler is 63 years old, has fished for 11 years, is a member of the Penobscot fishing club, faces low trip costs to the Penobscot of $37, and took 4 trips to the Penobscot.

Maine sites falls by 76%, and the probabilities for the Canadian sites all fall by 33%. IIA is retained within the two regions, and the higher level of substitution among Maine sites is a reasonable result. The probability of visiting the Penobscot increases by 88% when the catch doubles. To eliminate IIA assumptions entirely, different random α's could be estimated for each alternative, rather than for each region.

3.4 Models 4 and 5: heterogeneity in the stochastic component

Three approaches were investigated to allow heterogeneity in the random component of utility: 1) individual-specific scales; 2) group-specific scales; 3) and a random scale parameter. Compared to Model 1, all three resulted in significant reductions in the likelihood function and different monetary values. The results from two of those models, Model 4 (group scales) and Model 5 (a random scale) are presented below.

A model attempting to estimate individual-specific s_i's was run, but it only converged when a restrictive upper bound was placed on the scales, suggesting that the likelihood is monotonically increasing in the scale for certain individuals. The Hessian for the full model would not invert, although inversion was obtained separately for the β's. When individuals were examined on a case-by-case basis, it was discovered that about 60% had undetermined scales. Johnson and Desvousges (1997) also estimate a model with individual-specific scales using choice experiment data and report difficulties with convergence, although they do not report the proportion of individuals for whom the model did not converge. These findings are not surprising; as noted above, the ML estimator may not even exist for some individuals. Below, two alternatives to the individual-specific method are discussed, both of which have desirable features.

Although Johnson and Desvousges (1997) state that individual-specific scales can indicate whether groups of respondents make random or repetitive choices, or are having trouble with the survey design in the case of choice experiments, the individual scales themselves contain no information about the type of person fitting these categories. An alternative that does allow the researcher to reach conclusions about how scale varies across types of individuals is the use of different scale parameters for different types of groups.[16] This specification is also much easier to estimate because it reduces the number of scales to be estimated considerably.

Model 4 examines whether scales vary significantly based on age, experience, and club status. The Atlantic salmon anglers were divided into eight groups on the basis of the mean values of age and years of experience (47 and 6.5, respectively) and club status. Each angler was assigned a corresponding group-specific scale, and one scale was normalized to one to achieve identification.[17] The estimated parameters are reported in Table 1, and a likelihood ratio test shows that Model 4 is statistically superior to Model 1. For models with s's that vary, E(CV)s are a function of the scales:[18]

$$E(CV_i) = [1/(s_i\beta_0)] \times [\ln(\sum_{j=1}^{9} \exp(s_i V_{ji}^{0})) - \ln(\sum_{j=1}^{9} \exp(s_i V_{ji}^{1}))], \qquad \textbf{(13)}$$

Again, the mean E(CV)s are higher for Model 4, but only slightly as compared to Model 1. They are not statistically significantly different from the Model 1 means.

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[16] Note that an alternative to group scales would be to estimate scales as a nonnegative function of individual characteristics (see, for example, Cameron and Englin (1997) and Morey and Rossmann (1999)).

[17] The scale was fixed for the younger, inexperienced anglers who are not members of a club. They are the most numerous and took approximately the average number of trips for the sample. As a result, they had a large influence on the likelihood function of Model 1, the source of the starting values for Model 4.

[18] If there is only one alternative in each state of the world for the proposal being evaluated, the s's drop out of the formula for E(CV), although the estimation of β is still affected by the presence of heterogeneous scales in the likelihood function.

The club members as a group have the smallest random component variance, which suggests that they are very careful and systematic about fishing decisions. This is consistent with membership of a fishing organization. Of club members, younger anglers have smaller random components, but of the nonclub group, older anglers have smaller random components. The group scales range from 0.94 to 1.27.

Model 4 is estimated under the assumption that β does not vary across anglers, only $\sigma_{\epsilon i}^2$ varies (or similarly, that parameter proportionality holds). Section 2.5 discussed why individual-specific models cannot usually be estimated for revealed preference data, but group-specific models, where all parameters are allowed to vary across groups, may be identified if there are multiple individuals in each group with adequate variability in choices and with each facing a large number of choice occasions. Group models can be used to test the hypothesis of parameter proportionality (which is empirically indistinguishable from testing that preference parameters are the same across individuals, but only variances of the stochastic term differ) by adding up the log-likelihoods across the group models and comparing to a model with group-specific scales (Swait and Louviere, 1993). Parameter proportionality could not be tested here.[19]

Louviere (1996) notes that parameter proportionality is retained consistently across different types of data sets in numerous studies. If that finding extends to types of individuals, then using group scales is an appropriate way to address heterogeneity. Even in cases where parameter proportionality is statistically rejected, Louviere suggests that modeling only error variability will account for most of the heterogeneity. However, the significance of Model 3 suggests that parameter proportionality may not hold. Because s_i and β_i are confounded in a MNL

[19] Of eight group-specific models using the group definitions listed above, inversion was obtained for only two, primarily because of the small number of anglers in some groups and the small number of trips taken to the Canadian sites (only 34 across the sample, and zero in several groups).

model, if parameter proportionality is rejected, it is not possible to discern whether: 1) both parameters and scales vary, versus 2) just the parameters vary on the basis of individual-specific estimates of s_i and β_i (Swait and Louviere, 1993). However, as noted by Morey and Rossmann (1999), the model would be identified if s_i and β_i were estimated as functions of individual characteristics, or if both s and a subset of the elements of β were randomized.

Model 5 takes a different approach. While it is assumed that the s's vary across people, it is also assumed that they vary unsystematically from the researcher's perspective. Using a similar procedure to Model 3, s is assumed to be a random scale parameter with some distribution. The lognormal distribution is chosen to restrict $s_i > 0 \; \forall \; i$. To obtain identification, the median scale is fixed at one (by setting the mean of $\ln(s) = 0$). Anglers whose choices are rational and appropriately sensitive to characteristics of alternatives will have scale parameters close to the normalized value of one (Johnson and Desvousges, 1997). Those making random choices or those who do not care about the alternatives or their characteristics will have smaller scales; those for whom the model predicts extremely well, or who make repetitive choices, will have larger scales.

Again, 2,500 draws were used to minimize simulation noise. Given the lognormal distribution, the following formulas can be used to determine the mean and standard deviation of the random scale: $E(s) = exp(\sigma_{\ell s}^2/2)$; and $\sigma_s = exp(\sigma_{\ell s}^2/2) \times \sqrt{[exp(\sigma_{\ell s}^2) - 1]}$, where $\sigma_{\ell s}$ is the estimated standard deviation of $\ln(s)$. The mean s is 1.23, and the standard deviation of s is 1.99. Model 5 is statistically superior to Model 1. E(CV)s were simulated, and again the mean (and median) E(CV)s for doubling the catch rate are larger in absolute value than Model 1. For the site-deterioration scenarios, the means and medians are significantly smaller.

4. Conclusions

Several methods to incorporate heterogeneous preferences have been proposed to generalize the restrictions inherent in assuming homogeneity. These methods address four broad category types of heterogeneity: 1) systematic heterogeneity in the deterministic component of utility; 2) random heterogeneity in the (formerly) deterministic component; 3) systematic heterogeneity in the stochastic component; and 4) random heterogeneity in the stochastic component. While each of these types is dealt with individually in this paper, multiple types could be dealt with at once to reduce model restrictiveness and to allow for a much richer treatment of heterogeneity. One could envision an even more general model that combines the interaction and random parameters of Model 3 with the random scale of Model 5.

An important empirical finding in this paper is that restricting preferences to be homogeneous tends to result in significantly different mean expected consumer surplus and has important implications for the range of expected values as well. In some cases, mean E(*CV*)s for models incorporating heterogeneity were not statistically different from the means from Model 1 that does not have the features. However, in all cases allowing heterogeneity significantly improved model fit, which alone justifies use of the methods. Also, heterogeneity results in larger ranges in the E(*CV*)s across the sample, which is an implication of the model allowing for a wider range in individual behavior.

The systematic heterogeneity methods should be used where possible to allow the researcher to reach conclusions about subgroups of the population, which may be relevant for environmental policy targeting different types of recreationists. Systematic heterogeneity allows the researcher to assess the distributional impacts of policies. However, the random logit scale parameter provides the researcher a way to allow for variation in the distribution of the random component across individuals without the potential biases associated with estimating the scale as a function of covariates, or the difficulties associated with individual-specific scales.

Final model selection can depend on a mix of economic theory and intuition combined with empirical comparisons. In developing a model with heterogeneous preferences, it is important to consider the types of individuals in the sampling frame. How they differ in terms of geographic proximity, socioeconomic variables such as income and education, and avidity in terms of dependent variables such as number of recreational trips, and how responses differ to attitudinal questions, may provide insight on whether (and which) preference parameters should be expected to vary much across individuals, and whether those variations can be observed. These same factors, plus written and verbal comments perhaps, might be used to assess the level of coherence in decision-making and interest in the activity, and therefore could be used to decide whether iid assumptions about the random components are reasonable. As heterogeneity features are added to the basic model, their relative importance and impact can be evaluated not only on the basis of the likelihood function, but other factors including predictive power, and the robustness of parameters and other model results such as consumer surplus.

5. References

Abramowitz, M. and I. Stegun, *eds*. 1965. *Handbook of Mathematical Functions: With Formulas, Graphs, and Mathematical Tables*, New York: Dover Publications.

Adamowicz, W., J. Louviere, and J. Swait. "Introduction to attribute-based stated choice methods," final report submitted to the Resource Valuation Branch, Damage Assessment Center, NOAA, purchase order 43AANC601388 (January 1998), 44 p.

Aptech Systems, Inc. (1996) Gauss Applications: Maximum Likelihood *4.0.18*. 23804 South East Kent-Kangley Rd., Maple Valley, WA 98038.

Beggs, S., S. Cardell, and J. Hausman. 1981. "Assessing the potential demand for electric cars," *Journal of Econometrics* **16**, pp. 1-19.

Ben-Akiva, M. and T. Morikawa. 1990. "Estimation of switching models from revealed preferences and stated intentions," *Transportation Research A* **24A**, pp. 485-95.

Ben-Akiva, M., J. Walker, A.T. Bernardino, D.A. Gopinath, T. Morikawa, and A. Polydoropoulou. 1997. "Integration of choice and latent variable models," University of Texas, Austin working paper (October, 1997), 26 p.

Boxall, P. and V. Adamowicz. "Heterogeneity of preferences for environmental goods and services," University of Alberta working paper (September 11, 1998), 43 p.

Brownstone, D. and Train, K. "Forecasting new product penetration with flexible substitution patterns," University of California, Berkeley working paper (October, 1996), 24 p.

Cameron, T.A. and J. Englin. 1997. "Respondent experience and contingent valuation of environmental goods," *Journal of Environmental Economics and Management* **33**, pp. 296-313.

Chamberlain, G. 1984. "Panel data," in *Handbook of Econometrics Volume II* (Z. Griliches and M. Intrilligator, eds.), North-Holland, New York.

Fowkes, T. and M. Wardman. 1988. "The design of stated preference travel choice experiments," *Journal of Transportation Economics and Policy* (January), pp. 27-44.

Hausman, J. and D. Wise. 1978. "A conditional probit model for qualitative choice: discrete decisions recognizing interdependence and heterogeneous preferences," *Econometrica* **46**(2), pp. 403-26.

Herriges, J. and C. Kling. 1995. "An empirical investigation of the consistency of nested logit models with utility maximization," *American Journal of Agricultural Economics* 77, 875-84.

Johnson, F.R. and W.H. Desvousges. 1997. "Estimating stated preferences with rated-pair data: environmental, health, and employment effects of energy programs," *Journal of Environmental Economics and Management* **34**, pp. 79-99.

Layton, D. and G. Brown. "Heterogeneous preferences regarding global climate change," prepared for the Electrical Power Research Institute, Palo Alto, CA through Industrial Economics, Inc., Cambridge MA (undated), 33 p.

Louviere, J. "Combining revealed and stated preference data: the rescaling revolution," prepared for the Association of Environmental and Resource Economists, Lake Tahoe (June 2, 1996), 35 p.

Louviere, J. and J. Swait. "Separating weights and scale values in conjoint tasks using choices of best and worst attribute levels," University of Sydney working paper (August, 1997), 35 p.

McFadden, D. 1986. "The choice theory approach to market research," *Marketing Science* 5(4), pp. 275-97.

Morey, E. 1981. "The demand for site-specific recreational activities: A characteristics approach," *Journal of Environmental Economics and Management* 8, 345-371.

Morey, E. 1999. "TWO RUMs UnCLOAKED: nested-logit models of site choice and nested-logit models of participation and site choice," in *Valuing the Environment Using Recreation Demand Models* (C. Kling and J. Herriges, eds.), Edgar Elgar Publishing Ltd.

Morey, E., W.S. Breffle, R.D. Rowe, and D.M. Waldman, "Revised Report and Rebuttal: Assessment of Damages to Anglers and Other Recreators from Injuries to the Upper Clark Fork River Basin," Report prepared by Hagler Bailly Consulting for the State of Montana, Natural Resource Damage Litigation Program (1995).

Morey, E. and K.G. Rossmann. "Estimating the willingness to pay for reducing acid deposition injuries to cultural resources: choice experiments and heterogeneous preferences," University of Colorado working paper (1999), 23 p.

Morey, E., K.G. Rossmann, L. Chestnut, and S. Ragland. "Modeling and estimating WTP for reducing acid deposition injuries to cultural resources: using choice experiments in a group setting to estimate passive-use values," forthcoming as Chapter 10 in *Valuing Cultural Heritage: Applying Environmental Valuation Techniques to Historic Buildings, Monuments and Artifacts* (S. Narvud and R. Ready, eds.), Edward Elgar Publishing, Ltd.

Morey, E., R. Rowe, and M. Watson. 1993. "A repeated nested-logit model of Atlantic salmon fishing," *American Journal of Agricultural Economics* 75, 578-92.

Phaneuf, D., C. Kling and J. Herriges. "Valuing water quality improvements using revealed preference methods when corner solutions are present," Iowa State University working paper (July 1, 1998), 17 p.

Pollack, R. and T. Wales. 1992. *Demand System Specification and Estimation*, New York: Oxford University Press.

Revelt, D. and K. Train. 1998. "Mixed logit with repeated choices: households' choices of appliance efficiency level," forthcoming *Review of Economics and Statistics*.

Shaw, W.D. and M. Ozog. "Modeling overnight recreational trip choice: Application of a repeated nested multinomial logit model," Department of Applied Economics and Statistics, University of Nevada, Reno working paper (1996).

Stern, S. 1997. "Simulation-based estimation," *Journal of Economic Literature* (December).

Swait, J. and J. Louviere. 1993. "The role of the scale parameter in the estimation and comparison of multinomial logit models," *Journal of Marketing Research* **30**, pp. 305-14.

Swait, J., J. Louviere, and M. Williams. 1994. "A sequential approach to exploiting the combined strengths of SP and RP data: application to freight shipper choice," *Transportation* **21**, pp. 135-52.

Train, K. 1998. "Recreation demand models with taste differences over people," *Land Economics* **74**(2).