Investigating Preference Heterogeneity in a Repeated Discrete-Choice Recreation Demand Model of Atlantic Salmon Fishing*

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Marine Resource Economics, Volume 15, pp1-20, 2000

Keywords: preference heterogeneity, random parameters, recreation demand, discrete-choice travel cost model, complete demand system, logit, Atlantic Salmon fishing

Abstract: Estimating a demand system under the assumption that preferences are homogeneous may lead to biased estimates of parameters for any specific individual and significantly different expected consumer surplus estimates. This paper investigates several different parametric methods to incorporate heterogeneity in the context of a repeated discrete-choice model. The first is the classic method of assuming utility to be a function of individual characteristics. 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. Simulation noise is discussed. Finally, methods are proposed to relax the assumption that the unobserved stochastic component of utility is identically distributed across individuals. For example, randomization of the logit scale, which is a new method, allows noise levels to vary across individuals, without the added burden of explaining the source using covariates. The application is to Atlantic salmon fishing, and expected compensating variations and changes in trip patterns are compared across the models for three policy-relevant changes in fishing conditions at the Penobscot River, the best salmon fishing site in Maine.

* The authors thank Jose Canals, Nick Flores, Keith Maskus, Kathleen Rossmann, Don Waldman, Marty Walter, three anonymous reviewers, and the participants of the 1999 W-133 Regional Research Meeting in Tucson for comments and stimulating discussion. Thanks also to Bob Rowe of Stratus Consulting for providing the data set.

Introduction

A common assumption in random utility models of the demand for environmental amenities is homogeneity of preferences. That is, the deterministic portion of utility is assumed not to vary across individuals, and the variance of the random component is assumed to be iid. Incorrectly restricting preferences to be homogeneous, if in fact preferences do vary across individuals, will lead to biased parameter estimates for any specific individual, potentially resulting in dramatically different mean consumer surplus estimates for changes in characteristics such as catch rates at recreational fishing sites.[1]

The object of the paper is to discuss and compare different methods of introducing preference heterogeneity into a repeated discrete-choice model. The models presented are all utility-theoretic and explain both participation and site choice. The application is to recreational Atlantic salmon fishing using revealed preference (RP) data.[2] The data used in this study were used by Morey, Rowe, and Watson (1993) to estimate a three-level repeated nested logit model of participation and site choice with income effects, and several other related models. Their models, however, do not allow heterogeneity of preferences for site characteristics or heterogeneity of the logit scale.[3]

To examine preference heterogeneity in isolation, we introduce different forms of heterogeneity into a logit model rather than a nested-logit model or a probit model. Adding preference heterogeneity into either of these other types of models using any of the techniques presented here is straightforward, but would complicate the presentation and discussion. As a digression, introducing preference heterogeneity by incorporating group-specific random parameters, which is one of the methods we present, can achieve some of the same goals as assuming a nesting structure (in particular, the relaxation of *Independence of Irrelevant Alternatives* (*IIA*) properties), so could be considered a substitute for a nested-logit model.

The first and commonly used “classic” method of incorporating heterogeneity interacts demand parameters with observable socioeconomic characteristics of the individual. Utility effectively becomes a function of characteristics that vary across the sample. Classic models include income-effects models and all other models that make utility a function of individual characteristics. A different technique assumes that preference parameters for all individuals are drawn randomly from some known probability distribution function (PDF), although the parameters for any specific individual are unknown. In addition to introducing preference heterogeneity, *Random parameters logit* (*RPL*) is appealing, because it allows correlation of random disturbances across choice occasions.

A contribution of this paper is the introduction of a random logit scale parameter. This parameter addresses varying noise levels in choice-making across recreationists without the added burden of having to explain the source of noise using individual characteristics that may or may not be correlated with the noise. The method also avoids econometric difficulties associated with trying to estimate individual-specific scales. The proposed random scale approach is contrasted with other scaling approaches. Varying scales are empirically indiscernible from *parameter proportionality*, where the demand parameter vector only varies across individuals by a factor of proportionality.

We find that restricting preferences to be homogeneous often leads to significantly different mean consumer surplus estimates. For models that include socioeconomic characteristics to address heterogeneity, preferences vary as a function of these characteristics in plausible ways.

Techniques to Accommodate Preference Heterogeneity

Heterogeneity of preferences can be addressed either through a vector of marginal utilities (denoted β_i for individual *i*) incorporating demand parameters, 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 β to vary across individuals up to a factor of proportionality, because one specification is a reparameterization of the other (Swait and Louviere 1993).

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 the alternative that provides the greatest utility from J alternatives. The utility individual i receives on choice-occasion t if he chooses alternative j is:

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

Assume the term V_{ji} is deterministic. It is a linear function of a vector of explanatory variables x_{ji} associated with angler i and alternative j that are time-invariant, taking the form: $V_{ji} = \beta_i' x_{ji}$.[4] The ϵ's vary from period to period and across individuals in a way the researcher cannot observe.

Assume $,_{jti}$ is independently drawn from a univariate *extreme value distribution* with the cumulative distribution function:

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

where s_i is a positive scale.[5] This distribution has $E(,_i) = (0.57721/s_i)$ and $V(\epsilon_i) = \sigma^2_{\epsilon i} = \frac{\pi^2}{6s_i^2}$. The probability that individual i will choose alternative j on choice-occasion t is:

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

for all t. Given this distributional assumption, the observed number of trips to each site by individual i (y_{ji}) has a multinomial distribution.

Homogeneity of preferences is defined as $\$_i = \$$ (*i.e.*, effects on utility of changes in site characteristics do not vary across anglers either systematically or randomly) and $s_i = s$ ¼ i. Preference homogeneity implies that the random components are independent and identically distributed. This restrictive assumption means that the error variances across anglers are assumed to be the same and that there is no correlation in random components across choice occasions for a given angler.

Under homogeneity, let $s = 1$ without loss of generality, the usual assumption in logit models. Later, the scale parameter, 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 s to vary across individuals is empirically equivalent to allowing $\$$ to vary up to a factor of proportionality.

Utility as a Function of Individual Characteristics

This and the following section relax the assumption that $\$_i = \$$ ¼ i, while maintaining the assumption that $s_i = 1$ ¼ i. The utility angler i receives during choice-occasion t from alternative j is, therefore:

$$U_{jti} = \beta_i{}' x_{ji} + \epsilon_{jti},\ j = 1, \ldots, J. \tag{4}$$

The random component $,_{jti}$ is iid.

The classic way to allow preferences to vary across individuals is to interact individual socioeconomic characteristics, such as age, gender, or income, with model parameters (Adamowicz, Louviere, and Swait 1998). Pollack and Wales (1992) summarize methods of using demand parameters interacted with demographic variables. Two applications of this technique are Morey (1981) and Morey *et al.* (1999a). The first is a choice-share model of skiing in Colorado, in which the effects of ski area characteristics on utility 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 is a multitude of examples. Morey (1999), McFadden (1996), and Herriges and Kling (1997) discuss the theoretical underpinnings of income effects in logit models, and two empirical examples include Morey, Rowe, and Watson (1993), and Morey, Buchanan, and Waldman (1999). Models with income effects are not investigated here. Also, another literature investigating heterogeneity 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).

The main advantage of this technique is it allows $\$_i$ 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.[6] The primary drawback is that $\$_i$ 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. Also, multicollinearity is often a problem with too many interactions.

Random Parameters Logit (RPL)

Another way to incorporate heterogeneity through $\$$ is to assume that one or more parameters 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 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, Kling, and Herriges 1998). The random parameters model presented later, unlike the complete demand system of Phaneuf, Kling, and Herriges, 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 to model demand for a wide array of commodities and environmental amenities, including alternative-fuel vehicles (Brownstone and Train 1999); appliance efficiency (Revelt and Train 1998); 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, which is both its strength and weakness. As noted by Adamowicz, Louviere, and Swait (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 earlier. 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): $\beta_i = \boldsymbol{b} + \upsilon_i$. By assuming that υ_i is equal over choice-occasions for each individual, the unobserved components of utility become correlated.[7] By allowing for preference heterogeneity in this fashion, the restriction of independence associated with the nonrandom logit model is removed (Phaneuf, Kling, and Herriges 1998).[8] Train (1998) expects such persistence in the unobserved factors that affect utility over time and over sites.

If each angler's preferences (the $\$_i$'s) were known, the probability of observing angler *i*'s choices over the season would be:

$$P_i = \prod_{j=1}^{J} \left[\frac{e^{\beta_i' x_{ji}}}{\sum_{k=1}^{J} e^{\beta_i' x_{ki}}} \right]^{y_{ji}}. \tag{5}$$

However, the individual deviation vector L_i is unobservable. Only the PDF $f(\$)$ is assumed to be known, so the joint probability of observing angler *i*'s choices conditioned on L is the integral of Equation 5 over $\$$:

$$P_i = \int_{-\infty}^{\infty} \prod_{j=1}^{J} \left[\frac{e^{\beta_i' x_{ji}}}{\sum_{k=1}^{J} e^{\beta_i' x_{ki}}} \right]^{y_{ji}} f(\beta_i | \theta) d\beta_i \tag{6}$$

where 2 represents the parameters of the distribution of $\$$. 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 $f(\$)$ using a pseudo-random number generator:[9]

$$SP_i = \frac{1}{R} \sum_{r=1}^{R} \prod_{j=1}^{J} \left[\frac{e^{\beta_r' x_{ji}}}{\sum_{k=1}^{J} e^{\beta_r' x_{ki}}} \right]^{y_{ji}}, \tag{7}$$

where $\$_r$ is a single draw from $f(\$)$, and SP_i is the simulated probability of observing the individual's choices.

Heterogeneity of the Stochastic Component

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

As discussed in the initial section on the logit model, it is typical to assume that all individuals have stochastic components drawn from the same distribution. Under this assumption, all of the individual scales, the s_i's in equation 3, are the same and usually normalized to one. 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 new method proposed in this paper. One scale must be normalized (to one or some other value) to achieve identification in the model. Note that s_i is inversely proportional to $\sigma^2_{\epsilon i}$. 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).

Allowing s to be heterogeneous is empirically indistinguishable from *parameter proportionality* (Louviere 1996); that is, all $\$_i$'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.

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.[10] Incorporating heterogeneity of preferences through s is a much different exercise that also presents new challenges. For example, when merging k data sets, 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.

A 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 $\boldsymbol{s_i}$ 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 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 $s_i \to \infty$. Second, even if individual scales could be estimated, 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. Third, the random scale does not require estimation of the scale parameter as a function of individual covariates, which may lead to specification bias if the functional form is wrong.

Let the utility angler i receives during choice-occasion t from alternative j be:

$$U_{jti} = s_i \beta' x_{ji} + \epsilon_{jti},\ j = 1, \ldots, J. \tag{8}$$

where s_i is a scale parameter that varies across individuals. The vector x_{ji} contains factors observed by the researcher, β reflects the relative magnitudes of the marginal values of these observed factors to anglers, ϵ_{jti} captures factors the researcher does not observe, and s_i reflects the importance of the observed factors relative to the unobserved factors. The model allows people to differ in the importance (and value) they place on factors the researcher observes relative to the unobserved influences. A person whose choice is greatly affected by unobserved factors has a smaller s_i than a person whose choice is mostly affected by observed variables.

If the relative importance each angler places on observed variables (the s_i's) were known, the probability of observing angler i's choices over the season would be:

$$P_i = \prod_{j=1}^{J} \left[\frac{e^{s_i \beta' x_{ji}}}{\sum_{k=1}^{J} e^{s_i \beta' x_{ki}}} \right]^{y_{ji}}. \tag{9}$$

However, under the assumption the s_i's are unobservable, and only the PDF $g(s)$ is known, the joint probability of observing angler i's choices is the integral of Equation 9 over s:

$$P_i = \int_{-\infty}^{\infty} \prod_{j=1}^{J} \left[\frac{e^{s_i \beta' x_{ji}}}{\sum_{k=1}^{J} e^{s_i \beta' x_{ki}}} \right]^{y_{ji}} g(s_i|\psi) ds_i \tag{10}$$

where Q represents the parameters of the distribution of *s*.

Individual-specific Preference Parameters

In theory, it is possible to estimate individual-specific models in which no parameters are shared if the quantity of data is sufficient and the data exhibit enough variation.[11] 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 state preference data, with many observations per individual that exceed the number of parameters to estimate.[12] Individual-specific recreation demand models using RP data are difficult to estimate because of the typical lack of variation in choices and a small number of trips taken by many individuals. Interaction and RPL are good alternatives to individual-specific $\$_i$'s to admit heterogeneity in V_{ji}.

Repeated Logit Models of Salmon Fishing Participation and Site Choice that Allow Heterogeneity

The empirical application is a repeated logit recreation demand model of Atlantic salmon fishing participation and site choice. Some statistics summarizing the data set are included in table 1. 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 catch.

Table 1
Observed Trips, Expected Catch Rates, and Actual Fishing Costs
for Eight Atlantic Salmon Fishing Sites

River Group	Observed Trips	Expected Catch Rate per Trip	Average Trip Costs[1]
Maine Rivers:			
Penobscot	1994	0.102	$137
Machias	544	0.048	$239
Dennys	24	0.058	$246
Kennebec	132	0.074	$203
Saco	136	0.039	$288
Canadian Rivers:			
Nova Scotia	5	0.948	$806
New Brunswick	17	3.143	$827
Quebec	12	2.360	$885

[1] Includes value of time; these averages are only for trips actually taken.

Model 1: A Logit Model of Atlantic Salmon Fishing with Homogeneous Preferences for Site Characteristics

During a fishing season, an Atlantic salmon angler has a finite number of choice occasions, assumed to be 100,[13] 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 are composed of 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.

The deterministic portion of angler *i*'s conditional indirect utility function for fishing at site j, V_{ji}, is a function 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: $V_{ji} = \alpha_0(1 - D_j) + \alpha_{0C}D_j + \alpha_p(B_i - p_{ji}) + \alpha_1(1 - D_j)(catch_j) + \alpha_1(\alpha_{1C}D_j)(catch_j)$, $j = 1, ..., 8$. The expected catch rates at the Canadian sites are considerably higher than at the Maine sites. To account for this difference, the catch coefficient is a step function constructed by multiplying the catch parameter ("$_{1}$) by a catch-scale parameter ("$_{1C}$) if the site is in Canada. The price parameter, "$_{p}$, is interpreted as the marginal utility of money. The conditional indirect utility function 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} = "$_{09}$ + "$_{p}(B_i)$ + "$_{2}age_i$ + "$_{3}yrs_i$ + "$_{4}club_i$, 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.[14] This is a no-income-effects model; the budget cancels out of the choice-occasion probabilities.

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 2. 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 highly valued at Maine sites (where catch is lower) than at Canadian sites (where catch is higher). 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.

Table 2
Parameter Estimates[1]

Parameters	Model 1 Homogeneity	Model 2 Interaction	Model 3 RPL	Model 4 Group scales	Model 5 Random Scale
Fishing parameters[2]					
"$_{0C}$	4.409 (7.95)	5.124 (13.88)	2.971 (1.87)[6]	3.969 (7.46)	3.993 (7.48)
"$_{p}$	-0.0157 (-43.00)	-0.0154 (-42.61)	-0.0175 (-38.34)	-0.0144 (-29.99)	-0.0147 (-30.32)
"$_{1}$	15.834 (15.00)	32.363 (9.46)	39.220 (8.21)	14.808 (13.95)	12.466 (11.57)
"$_{1C}$	0.0620 (4.65)	0.0377 (5.87)	0.133 (1.45)	0.0630 (4.68)	0.0743 (4.51)
Participation parameters[3]					
"$_{09}$	2.296 (17.93)	3.726 (11.89)	4.517 (6.03)[6]	2.304 (18.47)	2.322 (18.10)
"$_{2}$	0.0200 (12.08)	-0.0121 (-1.87)	-0.0240 (-1.49)	0.0167 (8.94)	0.0218 (11.68)
"$_{3}$	-0.121 (-18.09)	-0.152 (-6.04)	-0.0577 (-1.09)	-0.100 (-12.10)	-0.134 (-15.60)
"$_{4}$	-0.647 (-13.52)	0.386 (2.14)	-0.404 (-1.01)	-0.868 (-12.80)	-1.0025 (-13.80)

Table 2 (continued)

Parameter Estimates[1]

Parameters	Model 1 Homogeneity	Model 2 Interaction	Model 3 RPL	Model 4 Group Scales	Model 5 Random Scale
Heterogeneity 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_{Rs}[5]					0.642 (16.15)
Likelihood ratio statistic (comparing to Model 1) [degrees of freedom]	NA	67.96 [3]	4054.20 [5]	47.30 [7]	1956.95 [1]

[1] Asymptotic *t*-statistics in parentheses.

[2] Fishing : $V_{ji} = \beta_0(1 - D_j) + \beta_{0C}D_j + \beta_p(B_i - p_{ji}) + \beta_1(1 - D_j)(catch_j) + \beta_1(\beta_{1C}D_j)(catch_j)$, $j = 1, ..., 8$; β_0 fixed at zero for identification in all models.

[3] Participation: $V_{9i} = \beta_{09} + \beta_p(B_i) + \beta_2 age_i + \beta_3 yrs_i + \beta_4 club_i$.

[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_{Rs} 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] β_{0C} (β_{09}) is the mean and σ_{0C} (σ_{09}) is the standard deviation of the normal distribution of the Canadian (nonparticipation) constant in Model 3.

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: increasing the catch rate 50%, 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:

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

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 3.[15] The mean seasonal E(CV) for increasing the catch by 50%, for example, is \$862, which is consistent with the very avid, serious nature of these recreational anglers. These anglers also pay high trip costs to go fishing (often in the hundreds or thousands of dollars).

Mean predicted trips to the Penobscot River under current conditions and for the two catch scenarios were also computed using the predicted probabilities (see equation 3) multiplied by the total number of choice occasions and are presented in table 4. Model 1 predicts that mean trips will increase by over nine if the Penobscot catch is increased by 50%, and decrease by almost six if the catch is halved.

Table 3
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
Increase catch 50%					
mean	\$862	\$1098[2]	\$1374[3]	\$874	\$856
95% confidence interval	\$681 to \$1060	\$907 to \$1317	\$1081 to \$1687	\$717 to \$1117	\$571 to \$1213
median	\$715	\$428	\$679	\$742	\$378
minimum	\$1	-\$35	-\$13	\$2	\$1
maximum	\$2977	\$7563	\$9031	\$3219	\$4664
Halve catch					
mean	-\$470	-\$521	-\$743[3]	-\$475	-\$164[3]
95% confidence interval	-\$537 to -\$408	-\$587 to -\$452	-\$920 to -\$594	-\$563 to -\$426	-\$220 to -\$124
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	-\$230[3]
95% confidence interval	-\$968 to -\$854	-\$1001 to -\$887	-\$1603 to -\$1072	-\$1008 to -\$872	-\$312 to -\$174
median	-\$638	-\$627	-\$900	-\$681	-\$146
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.

Table 4
Mean Predicted Trips to the Penobscot Under Different Penobscot Catch Scenarios

Model	Current Conditions	Increase Catch 50%	Halve Catch
Observed	13.29[1]	NA	NA
Model 1 – Homogeneity	12.36	21.56	6.39
Model 2 – Interaction	12.44	22.76	6.02
Model 3 – RPL	14.87	24.54	7.76
Model 4 – Group Scales	12.29	21.46	6.30
Model 5 – Random Scale	12.03	27.95	5.06

[1] Data were truncated by number of choice occasions (maximum of 100). Before truncation the mean was approximately 14 trips.

Model 2: A Logit Model with the Effect of Catch 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 change in utility from a change in catch is a linear function of age, years of experience, and the club dummy. The conditional indirect utility functions for the fishing alternatives become: $V_{ji} = \alpha_0(1 - D_j) + \alpha_{0C}D_j + \alpha_p(B_j - p_{ji}) + \alpha_1(1 - D_j)(catch_j) + \alpha_1(\alpha_{1C}D_j)(catch_j) + \gamma_1(1 - D_j)(age_i)(catch_j) + \gamma_2(1 - D_j)(yrs_i)(catch_j) + \gamma_3(1 - D_j)(club_i)(catch_j) + \gamma_1(\alpha_{1C}D_j)(age_i)(catch_j) + \gamma_2(\alpha_{1C}D_j)(yrs_i)(catch_j) + \gamma_3(\alpha_{1C}D_j)(club_i)(catch_j)$, $j = 1, ..., 8$.

Parameter estimates reported in table 2 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. Some individuals enjoy fishing for its solitude and relaxation rather than its action and social interactions. Two individuals in the sample who are older and are not club members have negative marginal utility for catch, and, thus, negative E(*CV*)s for catch improvements, which may be due to these factors or simply be an artifact of the linear model specification. Years of fishing experience is not a significant variable affecting site choice in Model 2.

Model 2 explains choices significantly better than Model 1, which is also true for Models 3 through 5. The mean E(*CV*)s for the sample as a whole, reported in table 3, are somewhat larger in absolute value for all Penobscot scenarios, although the medians are smaller. Note also that the mean trip response to changes in catch are also greater in Model 2 (see table 4). Club members tend to have the highest E(*CV*)s. 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. 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 utility from catch 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.

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 utility from catch is, again, allowed using the same interactions as in Model 2. In general it is preferable to explain why marginal utilities vary across anglers; it adds predictive power about the heterogeneity. Therefore, in Model 3, only the constants α_{0C} and α_{09} (the Canadian and nonparticipation constants, respectively) are randomized. These constants incorporate all of the site characteristics not explicitly included in the model, and one would expect preferences for these characteristics to vary across anglers. It would be possible, of course, have a catch parameter that is a function of both included angler characteristics and a random component if that were warranted, but doing so could lead to multicollinearity problems. 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.[16]

For Model 3, the conditional indirect utility functions for the fishing alternatives become: $V_{ji} = \alpha_0(1 - D_j) + (\alpha_{0C} + \mathrm{L}_{0Ci})D_j + \alpha_p(B_j - p_{ji}) + \alpha_1(1 - D_j)(catch_j) + \alpha_1(\alpha_{1C}D_j)(catch_j) + \gamma_1(1 - D_j)(age_i)(catch_j) + \gamma_2(1 - D_j)(yrs_i)(catch_j) + \gamma_3(1 - D_j)(club_i)(catch_j) + \gamma_1(\alpha_{1C}D_j)(age_i)(catch_j) + \gamma_2(\alpha_{1C}D_j)(yrs_i)(catch_j) + \gamma_3(\alpha_{1C}D_j)(club_i)(catch_j)$, $j = 1, ..., 8$. The conditional indirect utility function for nonparticipation is: $V_{9i} = (\alpha_{09} + \upsilon_{09i}) + \alpha_p(B_i) + \alpha_2 age_i + \alpha_3 yrs_i + \alpha_4 club_i$. The individual deviations from the means for the random parameters are denoted υ_{0Ci} and υ_{09i}. The probability of observing angler i's choices is:

$$P_i = \int_{-\infty}^{\infty} \prod_{j=1}^{9} \left[\frac{e^{V_{ji}}}{\sum_{k=1}^{9} e^{V_{ki}}} \right]^{y_{ji}} \phi(\upsilon_i) d\upsilon_i, \tag{12}$$

where υ_i is the vector of deviations for individual i, and ϕ is the bivariate normal density function with a zero mean vector and a diagonal covariance matrix with elements σ^2_{0C} and σ^2_{09}. Numerical simulation in Gauss was used to maximize the simulated log-likelihood.[17]

Model 3 explains choices significantly better than Model 2, and, in addition, σ_{0C} and σ_{09} have highly significant asymptotic t- statistics. The parameter estimates for the RPL are reported in table 2.[18] The mean estimates tend to be larger than those from Model 2. In Model 2, the error term contains the random component (υ) of the parameters, so the variance of ε is greater than in Model 3, where υ is treated separately (Revelt and Train 1998). Because the value of s is normalized to one in both models, b increases in Model 3 so that V_{ji} is larger relative to the variance of the stochastic term. 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, Kling, and Herriges 1998; and Layton and Brown 1998).

Note also that the significance levels of other Canadian and nonparticipation parameters are generally lower in Model 3. It is possible the random parameters for Canada and nonparticipation are picking up heterogeneity effects that were attributed to observed variables in the nonrandom model.

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

$$E(CV_i) = \frac{1}{R} \sum_{r=1}^{R} (1/\alpha_p) \times [V_{ri}^0 - V_{ri}^1]. \tag{13}$$

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 3 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. Responsiveness of the mean number of trips to the Penobscot when catch changes in table 4 (based on simulated probabilities in this model) is comparable to Model 2.

Model 3, with its group-specific random intercepts, causes the random terms within a group to be more correlated with each other than they are with the random terms in alternatives in other groups.[19] This is a property it shares with nested-logit model; it relaxes IIA in terms of the ratio of probabilities (see McFadden and Train 1998). For example, consider a representative angler.[20] Model 2 (a nonrandom model) predicts if the catch rate at the Penobscot increases by 50%, trips to all of the other sites will decrease by the same amount (31%), as a result of IIA. In contrast, with Model 3 if the catch rate at the Penobscot increases by 50%, the probability of visiting any of the other Maine sites falls by 48%, and the probabilities for the Canadian sites all fall by 16%. IIA is relaxed across the two regions but not within either region. The higher level of substitution among Maine sites is a reasonable result. To eliminate IIA assumptions entirely, different random "'s could be estimated for each alternative, rather than for each region.

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 (groups are defined here using socioeconomic variables); and 3) a random scale parameter. Compared to Model 1, all three resulted in significant increases in the likelihood function and different monetary values. The results from two of those models, Model 4 (socioeconomic group scales) and Model 5 (a random scale) are presented below.

Before estimating Models 4 and 5, we attempted to estimate a model with individual-specific s_i's, 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 this model would not invert, although inversion was obtained separately for $ holding the scales fixed. When individuals were examined on a case-by-case basis, it was found that about sixty percent of the individuals in the sample had either scales or standard errors that could not be estimated. 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 exist for some individuals. Models 4 and 5 are two alternatives to the individual-specific method, and both have desirable features.

While 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 (Johnson and Desvousges 1997), the individual scales themselves contain no information explaining why they vary across individuals. 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 groups (Model 4); this model is much easier to estimate than a model with individual-specific scales because it has considerably fewer parameters.[21]

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.[22] The probability that individual *i* (in group g_i, g_i 0 [1, ..., 8]) will choose alternative *j* on choice-occasion *t* is:

$$Prob_{jti} = \frac{e^{s_{g_i} V_{jti}}}{\sum_{k=1}^{J} e^{s_{g_i} V_{kti}}}. \tag{14}$$

The estimated parameters are reported in table 2. For models with *s*'s that vary, E(*CV*)s are a function of the scales:[23]

$$E(CV_i) = [1/(s_{g_i} \alpha_p)] \times [\ln(\sum_{j=1}^{9} \exp(s_{g_i} V_{ji}^{0})) - \ln(\sum_{j=1}^{9} \exp(s_{g_i} V_{ji}^{1}))], \tag{15}$$

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

The club members as a group have the smallest random-component variance, which suggests that their preferences are well-refined as a function of observable variables included in the model. 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 $\$$ does not vary across anglers, only $\boldsymbol{\sigma}^2_{\epsilon i}$ varies. Louviere (1996) notes that parameter proportionality is retained consistently across different types of data sets in numerous studies. Even in cases where parameter proportionality is statistically rejected, Louviere suggests that modeling only error variability will account for most of the heterogeneity. Group-specific models 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 by adding up the log-likelihoods across the group models and comparing to a model with group-specific scales (Swait and Louviere 1993). Model 4 could not be tested for parameter proportionality because we could not estimate a separate model for each group.[24]

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 $s_i > 0$ ¼ i. To obtain identification, the median scale is fixed at one (by setting the mean of ln(s) = 0). Those making random choices with disregard to observed factors will have smaller scales; those with crystallized preferences for whom the model predicts well 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(F_{Rs}^2/2); and F_s = exp(F_{Rs}^2/2) × Þ[exp(F_{Rs}^2) - 1], where F_{Rs} is the estimated standard deviation of ln(s). The mean s is 1.23, and the standard deviation of s is 1.99. E(CV)s were simulated, and the mean E(CV) for increasing the catch rate is comparable to Model 1, although the range is much larger. For the site-deterioration scenarios, the means and medians are significantly smaller, possibly due to the fact that the random scale affects the price parameter. Model 5 yields the greatest responsiveness in mean trips to changes, both increases and decreases, in the Penobscot catch rate in table 4.

In Conclusion

Several methods to incorporate heterogeneous preferences have been proposed to generalize the restrictions inherent in assuming homogeneity. These methods address four broad categories 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 (with the exception of Model 3 which has both random parameters and classic heterogeneity), multiple types could be dealt with at once to reduce model restrictiveness and to allow for a much richer treatment of heterogeneity. An even more general model could be envisioned that combines the interaction and random parameters of

Model 3 with the random scale of Model 5. Incorporating 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.

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 if the wrong functional form is used, 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; 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 how) preferences should be expected to vary across individuals, and whether those variations can be observed. These factors, plus written and verbal comments, 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.

Endnotes

1. In practice the assumption of homogeneity is used because it can often lead to a consistent estimator of population mean preferences. However, Fowkes and Wardman (1988) demonstrate by simulation that taste variation may lead to significantly different mean parameter estimates in the presence of nonlinearities.
2. Morey and Rossmann (1999) have recently examined heterogeneity of preferences using stated preference (SP) data.
3. Parameter and consumer surplus estimates from Morey, Rowe, and Watson (1993) differ from the results in this paper because of different functional forms, model assumptions, and sample subsets.
4. The model can be generalized to allow time-variant explanatory variables, leading to a more complicated likelihood function.
5. For a comprehensive discussion of the extreme value distribution and its application to discrete-choice models, see Morey (1999).
6. Benefits can vary widely as a function of individual type. See, for example, Morey *et al.* (1999b).
7. Hausman and Wise (1978) were the first to incorporate correlation across choice occasions in the context of a random probit model.

8. Although the unobserved components of utility are correlated across choice occasions for a given individual, the utility for a choice occasion is not a function of decisions made in other choice occasions. For an example of a model with dynamic recreational decision-making, see Provencher and Bishop (1997), where time elapsed since the last fishing trip affects the trip decision.

9. If only a few elements of $ are randomized, other techniques to evaluate the integral, such as Gaussian quadrature, may be used to increase speed and accuracy (Abramowitz and Stegun 1965; Breffle, Morey, and Waldman 2000). See Stern (1997) for a discussion of simulated ML and its advantages.

10. 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 nonparametric approach for estimating scale parameters when different data sets are aggregated. Swait, Louviere, and Williams (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 to allow for the possibility that SP data reflect tradeoffs more robustly and, therefore, may contain less noise. Ben-Akiva and Morikawa (1990) also examine the differences between RP and SP data-generating processes using scales.

11. 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 in the logit model or to the probit model.

12. For examples, see Johnson and Desvousges (1997), and Beggs, Cardell, and Hausman (1981). 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.

13. Over 97% of sample anglers took 100 or fewer trips during the season.

14. The three constants, α_0, α_{0C}, and 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 utility function 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.

15. Also, estimated mean E(*CV*)s are compared for equality across different models that follow using Mansfield's (1980) two-sample test of means.

16. 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, Kling, and Herriges (1998) use a normal distribution. Train (1998) also allows the price parameter to be random and lognormally distributed. Revelt and Train (1999) and Layton and Brown (1998), however, acknowledge the potential undesirable effects on the distribution of the E(*CV*)s as a result of a random price parameter (because it is in the denominator of the *CV*

formula), and hold the price parameter fixed. Phaneuf, Kling, and Herriges (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.

17. A comment is warranted about the choice of the number of repetitions, *R*, which is not examined extensively in the literature. The simulated probability is unbiased with only one draw of $, although the simulated logarithm of the probability, and therefore the simulated log-likelihood function, are biased. Increasing the number of repetitions reduces the bias, 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, so that 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. Brownstone and Train (1999) 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).

18. 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 and data can be obtained from the first author.

19. By allowing the Canadian and nonparticipation constants to be random, the model addresses heterogeneity between individuals in terms of choosing a Canadian site over another alternative (a very small number of anglers account for the majority of Canadian trips, and most anglers did not visit Canada at all), and heterogeneity in terms of avidity (total fishing trips vary widely across anglers in the data). It would be possible to fix one of these parameters (for identification) and instead estimate a random Maine parameter, which would account for heterogeneity in choosing Maine over another alternative. Results from such a model would be expected to differ.

20. 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.

21. 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).

22. 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.

23. 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 $ is still affected by the presence of heterogeneous scales in the likelihood function.

24. 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 0 in several groups).

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