Chapter 18

Stated Preference Methods for Valuation of Forest Attributes

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The valuation methods described in this chapter are based on the idea that forest ecosystems produce a wide variety of goods and services that are valued by people. Rather than focusing attention on the holistic value of forest ecosystems as is done in contingent valuation studies, attribute-based valuation methods (ABMs) focus attention on a set of attributes that have management or policy relevance (Adamowicz et al. 1998a, Bennett and Blarney 2001). The attribute set might include, for example, measures of biological diversity, areas designated for timber production or set aside for conservation, size of timber harvesting gaps, or watershed protection measures. If human-induced changes in forest ecosystems can be meaningfully represented by a set of attributes, choices made by survey respondents among sets of alternatives can provide resource managers and policy makers with detailed information about public preferences for many potential states of the environment. If price is included as an attribute of the problem, a multidimensional valuation surface can be estimated for use in cost/benefit analysis.

In this chapter, we show how forest management systems can be modeled as sets of management attributes and how value tradeoffs among forest management attributes can be measured using survey methods. Because increasing public concern with the sustainable use of forest resources has placed forest management in the spotlight, we suggest using ABMs to provide public agencies with information relevant to the design of forest

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practice codes and alternative management systems. By using scientifically based survey designs, sampling methods, and analytical techniques, ABMs can provide policy makers with information on broad-based citizen preferences that complements information gathered in public meetings and can provide a balanced assessment of how the general public values changes in forest management and conservation.

The state of Maine serves as a case study for our approach. Maine is more heavily forested than any other state in the United States, and the forest products industry provides significant income and employment to Maine residents. In addition, recreation, hunting, fishing, and wildlife viewing values associated with the woods provide significant contributions to the economy and quality of life in Maine. In 1989, the state legislature passed a Forest Practices Act that sets standards for timber harvests. However, public concern with some provisions of the Act, particularly regarding clearcutting, led to a number of initiatives to modify the Act.' Although none of these initiatives has succeeded to date, it is clear that many among the voting public are dissatisfied with status quo forest practices and are seeking alternatives that reduce timber-harvesting impacts on the goods and services provided by Maine forests.

To develop a better understanding of the tradeoffs that residents of Maine were willing to make regarding timber harvesting practices, we conducted a survey based on a random sample of the population. Our intentions in conducting the survey were twofold. First, we wanted to gain a clearer understanding of how much people were willing to pay (WTP) for alternative timber harvesting practices. These results could then be used in a cost/benefit analysis of policy alternatives. Second, we recognized that the use of WTP studies for evaluating policy alternatives is controversial, and we wanted to assess the validity of our survey responses. Although issues surrounding the validity of WTP surveys have many dimensions, a major issue is whether or not WTP values are affected by the design of the WTP response format. Consequently, we designed our survey instrument so that we could compare alternative response formats.

Choice models are becoming increasingly popular for measuring the value of environmental goods. The basic idea is that underlying preferences are revealed by the choices that people make. Choice methods are consistent with random utility theory; therefore, economic benefits associated with changes in environmental services can be estimated. As shown in section 5, ranking models are a special form of choice and can be derived from a model of random utility maximization. In this chapter, we compare responses to choice and ranking questions.

First, we review the literature on using ABMs to value forest ecosystems and summarize conclusions that can be drawn from it. Second, we briefly review random utility theory and show how it is connected to the choice model. Third, we describe how to test hypotheses regarding the parameters of choice models estimated on independent sub samples, and we highlight the importance of understanding the scale parameter when comparing choice model parameter estimates. Fourth, we present our forest management experiment and interpret the results. Finally, we draw conclusions about using ABMs to inform forest management and policy decisions.

1. LITERATURE REVIEW

Applications of ABMs to forest valuation are relatively new, first appearing in the literature in the late 1990s. Various response formats are available for conducting attribute-based experiments, and the most popular formats (rating, ranking, and choice) have all been used to conduct forest valuation studies.*

Garrod and Willis (1997) used a ranking study to estimate the benefits of enhancing forest biodiversity. Generic standards of increases in forest biodiversity were used (no increase, low-medium increase, medium-high increase, high increase). Alternatives were constructed using the area of forest managed according to each biodiversity standard, and the price variable was tax cost. The results showed that respondents preferred a balance between conservation and commercial timber production and, in general, were not willing to pay higher taxes for the greatest level of forest biodiversity restoration.

Hanley et al. (1998) used a choice experiment to estimate the value of alternative forest landscapes. Their experiment included four attributes: forest shape (straight edges versus organic edges); felling gaps (large versus small-scale clear cuts); species mix (evergreen only versus a combination of evergreen, larch, and broadleaf species); and tax (the price variable). They found that the respondents preferred forests with organically shaped edges, small-scale felling gaps, and a diverse mix of species.

Adamowicz et al. (1998b) used a choice experiment to estimate passive use values for woodland caribou habitat in Alberta (woodland caribou rely on old-growth forests). Attributes used in their experiment included four levels for each of the following attributes: woodland caribou populations, wilderness area, recreation restrictions, forest industry employment, and changes in provincial income tax. They found that utility and WTP increased with increased caribou populations and wilderness area and decreased as more severe restrictions were placed on recreation options. Changes in forest industry employment did not have a significant impact on WTP.

Similar in design to an Alberta moose hunting study (Adamowicz et al. 1997), Boxall and MacNab (2000) studied the preferences of wildlife recreationists in Saskatchewan for different aspects of boreal forest management. The sample was split to identify preferences of wildlife viewers and moose hunters. Attributes included three levels for each of the following: opportunity to see wildlife species, evidence of moose populations, encounters with other recreationists, access within the recreation area, evidence of forestry activity, and driving distance. For both hunters and wildlife viewers, large straight-edged clearcut areas with no residual trees generated large decreases in trip values. However, small (maximum width 440 m), irregular-shaped cutover areas with scattered patches of residual trees generated positive trip values for both wildlife viewers and moose hunters.

Holmes et al. (1998) used a paired comparison method to evaluate ecotourism options and estimate the value of a remaining remnant of Atlantic Coastal Forest in the Brazilian state of Bahia. The study attributes included amount of forest cover, lodging options, level of traffic congestion, nature park attractions, daily expenditures, and user fees. The study reported that Brazilian tourists had a positive willingness to pay for the protection of 7,000 km^2 of the Atlantic Coastal Forest ecosystem, and WTP increased with recreation options (such as canopy walks) in the nature park.

Schaberg et al. (1999) used the rating method to evaluate preferences for attributes of national forest management plans. The experimental design was based on priority levels (low, medium, and high) for the following attributes: forest recreation, hunting and fishing, timber harvesting, water quality, and native ecosystems. A cost variable was not included in the design. They found that the ideal management plan would place high emphasis on ecosystem restoration and water quality protection, low emphasis on timber harvesting, and moderate emphasis on recreational opportunities.

Haefele and Loomis (2001a,b) used the rating method to estimate the value of changes in forest health. They included attributes for the number of acres infested by various forest pests, the percentage change in commercial timber harvests, the possible risk of water contamination from pesticide spraying, and the expected percentage change in recreation use. Similar to the Schaberg et al. (1999) study, they found a high level of concern with the water quality impacts of forest operations. This study also found that people preferred pest control programs that had minimal impact on commercial timber harvests.

Overall, then, we find evidence in previous studies that the general public is willing to pay for changes in forest management and timber harvesting operations that reduce the biological and amenity impacts on forest ecosystems. However, because only a limited number of forest preference studies have been conducted, many dimensions of citizen preferences for forest management remain unexplored. Future research needs to consider, among other things, how the social, economic, and natural resource context may influence preferences for forest attributes.

2. A RANDOM UTILITY FUNCTION

Our presentation of the choice modeling approach to forest valuation begins with a random utility function that can be used to link utility (a theoretical construct) with actual choices. A random utility function considers individual preferences (subscript n) to be the sum of systematic (V_{in}) and random (ε_{in}) components:

$$U_{in} = V_{in}(x_{in}, p_{in}; \beta) + \varepsilon_{in} \quad 18.1$$

where U_{in} is the true but unobservable utility associated with alternative i, x_{in} is a vector of attributes associated with alternative i, p_{in} is the cost of alternative i, β is a vector of preference parameters for the population, and ε_{in} is a random error term with zero mean.[3] In its simplest form, utility is represented as linear-in-parameters:

$$U_{in} = \sum_{k=1}^{l} \beta_k x_{ink} + \beta_p p_{in} + \varepsilon_{in} \quad 18.2$$

Differentiation of equation 18.2 shows that preference parameter estimates (a vector of βs) can be interpreted as marginal utilities: $\beta_k = \partial U_i/\partial x_{ik}$. The negative of the parameter estimate on cost, β_p, is interpreted as the marginal utility of money. The marginal rate of substitution between any two attributes k and 1 is easily computed ($MRS_{kl} = \beta_k/\beta_l$), and the implicit price (or marginal WTP) of attribute k is β_k/β_p.

3. CHOICE MODELS

The stochastic term in the random utility function shown in equation 18.1 allows probabilistic statements to be made about actual choices. Consider a choice set C containing $J > 2$ alternatives (such as J different recreation sites). The probability that a consumer will choose alternative i from choice set C can be expressed as a function of random utilities (McFadden 1973):

$$P_n(i) = P(U_{in} > U_{jn}) = P[V_{in} + \varepsilon_{in} > V_{jn} + \varepsilon_{jn}], \forall j \in C \qquad 18.3$$

Various probabilistic choice models can be derived from equation 18.3, depending on the assumption made about the distribution of the random error ε. The assumption that ε follows an Extreme Value Type 1 (EV1) distribution is often used, and the resulting model is referred to as multinomial logit (MNL).[4] This assumption is made purely for analytical convenience, as the difference between two EV1 variables is logistically distributed, and the logit distribution has convenient closed-form properties (Ben-Akiva and Lerman 1985).

Given this assumption, the probability of individual n choosing alternative i from the set C is written (using matrix notation and including cost in the x_n vectors):

$$P_n(i) = \frac{\exp(\mu\beta' x_{in})}{\sum_{j\in C}\exp(\mu\beta' x_{jn})} \qquad 18.4$$

where μ is a scale parameter (see section 5). If we let N represent the sample size, then the likelihood function for the MNL model is:

$$L = \prod_{n=1}^{N}\prod_{i\in C} P_n(i)^{y_{in}} \qquad 18.5$$

where

$$y_{in} = 1 \text{ if individual } n \text{ chose alternative } i$$
$$= 0 \text{ otherwise.}$$

Substituting equation 18.4 into equation 18.5 and taking the natural logarithm, the MNL model is estimated by finding the values of the βs that maximize the log-likelihood:

$$\ln L = \sum_{n=1}^{N} \sum_{i \in C} y_{in} (\mu\beta' x_{in} - \ln \sum_{j \in C} \exp(\mu\beta' x_{jn})) \quad 18.6$$

The major limitation of the MNL model is that data are subject to the Independence of Irrelevant Alternatives (IIA) property. This property requires "that for a specific individual the ratio of the choice probabilities of any two alternatives is entirely unaffected by the systematic utilities of any other alternatives" (Ben-Akiva and Lerman 1985:108). Simply stated, this property requires that equation errors are independent. That is, none of the unobserved factors influencing the choice of any alternative i can influence the choice of any other alternative j. This condition limits the substitution possibilities among alternatives.' However, if this property holds, it allows the analyst to estimate the probability of choosing new alternatives not included in the choice experiment simply by adjusting terms in the denominator of equation 18.4.

The goal of many ABM nonmarket valuation studies is to estimate welfare impacts so they can be used in management and policy analysis. ABMs provide quantitative measures of tradeoffs between attributes, including price. Thus, they can be used to estimate how much money would be required to make a person as well off after a change in attributes as they were before the change. The fact that ABMs provide estimates of the indirect utility function allows one to calculate welfare measures for improvements or decrements in utility.

Ben-Akiva and Lerman (1985) show that for a set of independent variables that are EVI-distributed with common scale (μ), the maximum is also EVI-distributed. As defined in equation 18.1, utility is characterized as the sum of a systematic and stochastic component. By assuming that the stochastic component is EVI-distributed, it can be shown that the expected value of maximum utility can be specified as

$$E(U) = \ln(\sum_{j=1}^{J} \exp(V_j)) + D \quad 18.7$$

where D is Euler's constant, and the other term is known as the log sum or inclusive value (Hanemann 1999, Morey 1999). This expression forms the basis for welfare measurement when multiple alternatives are available.

In the most general situation, compensating variation is computed as the difference between two expected values of maximum utility divided by the marginal utility of money ($\lambda = -\beta_p$):

$$CV=\frac{1}{\lambda}[\ln\sum_{j=1}^{J}\exp(V_j^1)-\ln\sum_{j=1}^{J}\exp(V_j^0)] \qquad 18.8$$

where the 0 superscript refers to the base situation (policy off), the 1 superscript to the altered situation (policy on), and J to the number of sites or locations included in the utility function. An example of this situation is the computation of compensating variation for a change in attribute levels for a set of recreation sites from the base situation to some altered levels. A simpler situation, as computed in this study, is the compensating variation for a change in attributes for a single site or location. In this situation, equation 18.8 reduces to:

$$CV=\frac{1}{\lambda}[V^1-V^0] \qquad 18.9$$

where V^0 and V^1 are the utility expressions for the base and altered cases. In the simplest situation, where interest focuses on the value of a change in a single attribute, and utility is linear-in-parameters as in equation 18.2, equation 18.9 reduces to the ratio of the attribute coefficient and the marginal utility of money.

4. RANKING MODELS

Ranking question formats offer a more complex form of choice responses, in which respondents are asked not simply to choose their most preferred alternative but to order alternatives from most to least preferred. This question format results in a series of responses from 1 to K for a set of K alternatives. In the standard model, the respondent is assumed to first choose the alternative that provides the greatest utility from the choice set. Then the second ranked alternative is chosen from the remaining choice set, and so forth until all alternatives are ranked. Marschak (1960) showed that this sequence of choices can be considered as the product of independent probabilities:

$$P[alt.1\ ranked\ \text{lst},\ alt.2\ ranked\ 2nd,\ldots,alt.K\ ranked\ fast] = P(1|1,2,3,\ldots,K)\bullet P(2|2,3,\ldots,K)\bullet\ldots P(K-1|K-1,K) \qquad 18.10$$

Then, if the IIA property holds, an MNL model can be substituted for each of the $K-$ I probabilities in equation 18.10, resulting in the standard rank-ordered logit model (Beggs et al. 198 1):

$$P(U_k > U_l > ... > U_K) = \prod_{k=1}^{K-1} \frac{\exp(\mu\beta' x_k)}{\sum_{i=k}^{K} \exp(\mu\beta' x_i)} \qquad 18.11$$

This formula implies that an observation of K ranked alternatives can be "exploded" into *K – 1* statistically independent choices, and that the probability shown in equation 18.11 is the product of the exploded choices.

The log-likelihood function for the rank-order model is the sum of ordinary MNL log-likelihoods over the exploded choices:

$$L = \sum_{k=1}^{K-1} \sum_{n=1}^{N} [\mu\beta' x_{kn} - \ln \sum_{i=k}^{K} \exp(\mu\beta' x_{in})] \qquad 18.12$$

where μ is typically set equal to one.

Ranking models ostensibly offer the advantage of providing more information than a standard choice model because of the additional information contained in the sequence of choices. From a statistical perspective, the additional information provided by rankings should lead to smaller standard errors for parameter estimates. However, experience has shown that error variance increases (scale decreases) as respondents proceed down through the sequence of choices.

5. UNDERSTANDING THE SCALE PARAMETER

Equations 18.4 and 18.11 show that in the MNL model the scale factor and the preference parameters are always represented in multiplicative form $\mu\beta$, so it is not possible to identify scale in any particular model. Because scale and preference parameters are always confounded, parameters estimated from different data sets should not be directly compared, because it is not clear whether differences are due to preferences, scale, or both. However, if data are available from more than one choice set, then it is possible to recover an estimate of relative scale parameters for the data sets. And, given an estimate of scale, it is then possible to test whether parameter vectors are the same up to a scaling constant.

The scale factor in a MNL model is inversely related to the variance of the equation error (where π is the mathematical constant 3.14 I 6.. .):

$$\sigma^2 = \pi^2 / 6\mu^2 \qquad 18.13$$

A larger scale is indicative of a smaller variance and, in turn, implies less noise and a better fitting model.[6] If, in a ranking task, respondents become fatigued or confused as they proceed through lower ranks, then the scale parameter would be expected to decrease (variance increases) as ranking depth increases. In an analysis of ranking data, Hausman and Ruud (1987) found a general decrease in scale with ranking depth, although the change in μ was not monotonic. Ben-Akiva et al. (1992) found that scale decreased with rank and recommended that data not be pooled in a single ranking model unless further testing indicated that parameter vectors are equal up to the scaling constants. They suggested a simple graphical method for identifying the scale parameters. This procedure is identical to a method proposed by Swait and Louviere (1993) for comparing multinomial logit models across independent data sets,

Notice in equation 18.10 that the first exploded rank is nominally identical to a choice question where respondents are asked to choose one item from a choice set containing K items. Consequently, not only is it possible to test the stability of preferences across different depths of ranking data, it is also possible to test the cross-validity of choice and ranking models using exploded rank data.

6. VALIDITY TESTS FOR CHOICE MODELS

If data are available from two or more choice sets (either independent sub samples from choice experiments or presumed independent choices in a ranking experiment), relative scale parameters can be recovered, and rescaled parameter vectors can be tested for equality. This can be accomplished by optimally rescaling the set of explanatory variables in one of the data sets.

Consider the case of two data sets X_1 and X_2 with common attributes. Let $\mu_1\beta_1$ represent parameter estimates from X_1, and let $\mu_2\beta_2$ represent parameter estimates from X_2. If both data sets reflect identical preferences ($\beta_1 = \beta_2$) but have different scales ($\mu_1 \neq \mu_2$), casual examination of the estimated coefficients would indicate that tastes were different (because $\mu_1\beta_1 \neq \mu_2\beta_2$). However, it is possible to estimate the relative scale parameter (μ_2/μ_1) and then test the hypothesis that $\beta_1 = \beta_2$ controlling for relative scale.'

Swait and Louviere (1993) show how to test the joint hypotheses: $H_1: \beta_1 = \beta_2$ and $\mu_1 = \mu_2$ using a hvo-stage variant of the Chow test. The test proceeds by the following steps:

1. Make an initial estimate of μ_2/μ_1. This can be accomplished by regressing β_1 on β_2 or, more simply, by setting $\mu_2/\mu_1 = 1$.

2. Multiply data points in X_2 by μ_2/μ_1 and pool (vertically concatenate) the data with X_1.
3. Maximize the log likelihood function for the pooled data.
4. Repeat steps 2 and 3 for smaller and larger values of μ_2/μ_1.
5. Plot the values obtained from steps 2 through 4 until a peak is found for maximum likelihood as a function of μ_2/μ_1.
6. At the peak value for μ_2/μ_1, the data have been optimally rescaled.

The hypothesis $H_A : \beta_1 = \beta_2$ can then be tested using the likelihood ratio test statistic:

$$a, = -2[L_\mu - (L, + L_2)] \qquad 18.14$$

where L_μ is the log likelihood value for the optimally adjusted pooled data model, L_1 is the log likelihood value for the X_1 model, and L_2 is the likelihood value for the X_2 model.*

If the hypothesis $\beta_1 = \beta_2$ is rejected after optimally adjusting for the scale parameter, then it is clear that the data do not represent the same preferences. If this hypothesis is not rejected, parameters estimated from the pooled data can be used for analysis and inference. Further, if H_A is not rejected, it is possible to test the hypothesis that H_B: $\mu_1 = \mu_2$. This is simply accomplished by pooling X_1 and X_2 (unadjusted) and using the likelihood ratio test statistic:

$$a, = -2[L_p - L_\mu] \qquad 18.15$$

where L_p is the log likelihood value for the (unadjusted) pooled data.

7. THE FOREST MANAGEMENT EXPERIMENT

Our forest management experiment is based on data collected in a mail survey of Maine residents regarding their preferences for alternative timber harvesting practices. As described in the introduction, forest management in Maine is a controversial subject. After holding discussions with forest management experts in the State, and after focus groups conducted with randomly sampled citizens, we chose seven forest management attributes to include in the experiment (table 18.1). The number of attributes and levels we used resulted in a larger design space and more complex choice problems than those of previous forest valuation studies.

Table 18.1. Forest management attributes, levels, and names

Attributes	Levels	Variable Names
Forest road density	One road every mile	ROADS-I
	One road every ½ mile	ROADS-%
Live trees after harvest	No trees > 6-in. diam./ acre	LIVE-O
	153 trees > 6-in. diam./ acre	LIVE-1 53
	459 trees > 6-in. diam./ acre	LIVE-459
Dead trees after harvest	**Remove all**	DEAD-O
	5 trees/acre	DEAD-S
	10 trees/acre	DEAD-I 0
Max. size of harvest area	5 acres	HAREA_5
	35 **acres**	HAREA_35
	125 acres	HAREA_12.5
Available for harvesting	80%	HVST_80
	50%	HVST_50
	20%	HVST_20
Width of riparian buffers	500 ft. min.	H2O_500
	250 **ft. min.**	**I-120-250**
Slash disposal	Leave it where it falls	SLASH-LV
	Distribute along skid trails	SLASH-DST
	Remove all	SLASH NO

The management practices representing base level (most common) are shown in bold.

As can be seen, most of the levels included for forest management attributes represent more environmentally benign practices relative to the base level. Only two attributes (number of live trees remaining after harvest and maximum size of harvest area) include levels with greater and lesser environmental impact than the base level. Attributes were coded using effects codes with the base level of the attribute the omitted level.'

Descriptive information regarding the pros and cons of alternative management practices, as well as a description of the most common practice, was presented by enclosing an information booklet with the questionnaire. Line drawings were used to represent two levels of each management attribute to help respondents conceptualize the management activity being addressed. The first questions included in the questionnaire booklet were quiz questions to help us gauge how well respondents' understood the background information.

The context for evaluating management activities described the State purchasing a 23,000-acre parcel of forest land from a large forest land management company. Respondents were given a description of the parcel and provided with a map showing its approximate location. They were then presented with four management plans to consider for the parcel. Each management plan was composed of randomly assigned levels of each management practice. In addition, a monetary attribute was included in the design, which was a one-time increase in State income taxes to pay for the forest land purchase."

Alternative forest management plans were constructed using a completely randomized design across individuals. That is, attribute levels were randomly sampled from the entire design space and placed in potentially unique alternatives for each individual in the sample. Respondents were randomly assigned into sub samples for ranking and choice questions. For the ranking questions, respondents were asked to rank four management plans from most preferred to least preferred. For the choice question, respondents were asked to circle the letter of their most preferred management plan. An example of alternative forest management plans is shown below (table 18.2).[11]

Table 18.2. Sample forest management plans for the choice and ranking experiments

Attributes	Plan A	Plan B	Plan C	Plan D
Forest road density	1 every ½ mile	1 every mile	1 every mile	1 every ½ mile
Dead trees after harvest	5 trees/acre	5 trees/acre	Remove all	10 trees/acre
Live trees after harvest	459 trees/acre	153 trees/acre	459 trees/acre	No trees
Maximum size harvest opening	125 acres	125 acres	35 acres	5 acres
Proportion cut/ set-aside	20% cut/ 80% set-aside	50% cut/ 50% set-aside	50% cut/ 50% set-aside	20% cut/ 80% set-aside
Watershed protection	At least 250-A. buffer zone	At least 500-ft. buffer zone	At least 250-A. buffer zone	At least 500-ft. buffer zone
Slash disposal	Distribute along skid trails	Remove all	Leave it where it falls	Remove all
One-time tax increase	$400	$60	$140	$10

Preference parameters for the forest management attributes were estimated using MNL models for full ranks, exploded ranks 1 (choose one of four), exploded ranks 2 (choose one of three) and exploded ranks 3 (choose one of two), as well as an MNL model for responses to the choice question (table 18.3). Even a simple eyeball examination of the results provides valuable information. First, a comparison of the full ranks model with the exploded ranks models shows that the set of salient (statistically different than zero) attributes varied across the different specifications of the ranking model. It appears as though respondents searched for salient attributes in the management plans, and their focus shifted as they progressed through the ranking exercise. This may have resulted from the complexity associated with having to consider seven management attributes plus a tax price. We also note that the number of salient attributes decreased as ranking depth increased, and McFadden's R^2 for lower ranks were less than for exploded rank 1.[12] These indicators suggest that respondents became fatigued as they completed the ranking question. Based on our initial visual observation, the lack of consistent preferences across ranking depths suggests that ranking data should not be pooled to estimate a full ranks model.

A comparison of exploded ranks 1 and choose-one data, which are ostensibly identical response formats, provides substantial insight into preferences for forest management attributes. Here examination shows consistency regarding the saliency of management attributes: the same attributes have a statistically significant impact on respondent choices. The nonsalient attributes were also the same across response formats and included H2OZONE (the width of riparian buffers), ROADS (forest road density), and HAREA (maximum size of harvest area).[13]

The set of attributes that were salient in both response formats were tax price (TAX), the number of live trees remaining after harvest (LIVE), the number of dead trees remaining after harvest (DEAD), the proportion of the forest available for harvest versus set-aside (HVST), and the disposal of slash created by the harvesting operation (SLASH). Focusing first on the number of live trees remaining after harvest, the parameter estimate on LIVE_0 (no live trees > 6-in. diameter after harvest, or clear cutting) was negative and larger in magnitude than any other management attribute. Including a clear cutting alternative in the contingent management plan had a large negative impact on the conditional indirect utility of respondents, even though the word clear cut was not used in the survey. The parameter estimate for the omitted base level (153 trees > 6-in. diameter/acre left after harvest) was computed to be 0.3 11 in the exploded ranks 1 model and 0.3 15 in the choose-one model.[14] In both models, then, we identified a quadratic valuation function, where utility was maximized at the base timber harvest level. Utility decreased rapidly from the moderate harvest intensity level to the clearcut harvest level. Utility decreased less rapidly as harvest intensity decreased from moderate to light.

The number of dead trees remaining after harvest was a salient attribute in both the exploded ranks 1 and choose-one models, but the most preferred level was different between the two models (DEAD-5 versus DEAD 10, respectively). This pattern was also identified for the attribute representing the percent of the forest area available for harvest (HVST_20 versus HVST_50, respectively). Why this shift occurred between models is not clear. What is clear, however, is that respondents preferred more dead trees left after harvesting (which mimics one aspect of old-growth forest structure) and a greater proportion of forest area set-aside for conservation, relative to the base level. However, there was lack of convergence across response formats regarding the optimal level of these attributes.

Table 18.3. Parameters for MNL models estimated using ranking and choice data

Variable	Full Ranks (Std. Err.)	Exploded Ranks 1 (Std. Err.)	Exploded Ranks 2 (Std. Err.)	Exploded Ranks 3 (Std. Err.)	Choice (Std. Err.)
ROAD-1	0.108**	0.061	0.300***	-0.514	0.035
	(0.053)	(0.085)	(0.0093)	(0.109)	(0.076)
LIVE-O	-0.318***	-0.585***	-0.324***	0.016	-0.497***
	(0.074)	(0.133)	(0.126)	(0.145)	(0.114)
LIVE-459	0.115	0.274**	0.106	-0.089	0.182*
	(0.075)	(0.120)	(0.128)	(0.157)	(0.105)
DEAD-5	0.130*	0.324***	0.153	-0.195	0.123
	(0.074)	(0.125)	(0.132)	(0.162)	(0.103)
DEAD-10	0.147**	0.141	0.00004	0.455***	0.331***
	(0.073)	(0.125)	(0.132)	(0.165)	(0.101)
H2OZONE	0.030	0.072	-0.056	0.098	0.017
	(0.052)	(0.087)	(0.089)	(0.107)	(0.074)
HVST_20	0.214***	0.374***	0.075	0.170	-0.103
	(0.075)	(0.117)	(0.132)	(0.166)	(0.108)
HVST_50	0.024	0.010	0.030	0.070	0.357***
	(0.074)	(0.122)	(0.126)	(0.147)	(0.102)
HAREA_125	-0.008	0.178	-0.316**	0.072	0.021
	(0.074)	(0.118)	(0.135)	(0.162)	(0.108)
HAREA_5	-0.075	-0.109	0.145	-0.292*	-0.004
	(0.074)	(0.122)	(0.124)	(0.155)	(0.107)
SLASH-LV	0.123*	0.231*	0.168	-0.048	0.179*
	(0.073)	(0.121)	(0.131)	(0.159)	(0.106)
SLASH-DST	0.116	0.385***	-0.119	0.068	0.023
	(0.075)	(0.126)	(0.140)	(0.152)	(0.105)
TAX	-0.00090***	-0.00083***	-0.00096***	-0.00081***	-0.00152***
	(0.00011)	(0.00025)	(0.00025)	(0.00024)	(0.00027)
L(0)	—	-295.2807	-232.9058	-146.9472	-385.3898
L(β)	—	-251.3436	-210.4798	-132.0054	-332.1598
1-L(β)/L(0[redacted]	[redacted]	[redacted]	0.0963	0.1017 [redacted]	0.1381
N	212	212	212	212	278

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level.

The disposition of slash created by the harvest operation was also a salient attribute in the exploded ranks 1 and choose-one models. Again we identified a similar pattern: respondents preferred more environmentally benign practices for slash disposal relative to the base level (remove all slash), but there was lack of convergence across models regarding the optimal level for this attribute.

Results from the Swait and Louviere (1993) procedure for testing hypotheses regarding the equality of parameter estimates in MNL models confirm the results from the eyeball comparisons (table 18.4). The hypothesis that parameter estimates for choose-one (Cl) and exploded ranks 1 (ER1) are no different was rejected at the 95% confidence level.[15] We also found that parameter estimates for the exploded ranks data were not equal over all ranking depths. Although we rejected the hypothesis (at the 95% confidence level) that preference parameters for ER1 and exploded ranks 2 (ER2) are the same, we could not reject the hypothesis that preference parameters for ER1 and exploded ranks 3 (ER3) are the same. This is likely due to the relatively large standard errors associated with the ER3 model. Further, we found that model variance increased along with ranking depth. This result is consistent with the idea that respondents become fatigued as they complete a ranking task, reflecting findings reported by Hausman and Ruud (1987) and Ben-Akiva et al. (1992). These results lead us to formally conclude that exploded ranks data should not be pooled to estimate a full ranks model in our case.

Table 18.4. Results for hypothesis tests regarding parameter equality in MNL models: H_A ($\beta_1 = \beta_2$); H_B ($\mu_1 = \mu_2$)

Test	μ_1/μ_2	L_1	L_2	L_μ	λ_A	Reject H_A ?	L_p	λ_B	Reject H_B?
ER1: Cl	0.97	-251.34	-332.16	-596.33	25.66	Yes”	—		
ER1: ER2	1.82	-25 1.34	-210.48	-476.26	28.87	Yes[a]	—	—	—
ER1: ER3	2.22	-251.34	-132.01	-393.89	21.08	No”	-397.85	7.93	Yes[b]

[a] χ^2 statistic for 14 d.f. and 95% confidence level = 23.69
[b] χ^2 statistic for 1 d.f. and 95% confidence level = 3.84

Finally, estimates of compensating variation were computed using the parameter values for the choose-one model shown in table 18.2 and the formula shown in equation 18.9. We considered a reduced impact timber harvest alternative for the contingent forest versus a base level timber harvest alternative representing typical current management practices. We specified the reduced impact *(base* level) alternative to have the following attributes and levels: (1) 459 live trees > 6-in. diameter (153 live trees > 6-in. *diameter)* per acre remaining after harvest, (2) 10 dead trees *(no dead* trees) per acre remaining after harvest, (3) harvest permitted on 50% (80%) of the forest, and (4) leave slash where it falls (remove all slash). The value of the reduced impact timber harvest alternative, relative to the base level, was estimated to be $1,08 1.58. This is a per household lump sum amount.

8. SUMMARY AND CONCLUSIONS

Attribute-based stated preference methods are relatively new tools for environmental valuation. They can provide detailed information about citizen preferences for incremental changes in a set of environmental attributes under the control of managers and policy makers. ABMs seem eminently suitable for valuation problems in cost/benefit analyses of forest management and protection alternatives.

However, as with other stated preference methods, such as contingent valuation, the application of ABMs to environmental valuation is not trouble free. An important issue is the convergent validity of different response formats. In the case study reported in this chapter, convergent validity was not established for two nominally identical responses, choose-one and first rank. The lack of convergence may be due to differences in cognitive processes used to answer the questions. Future research needs to investigate the effect of decision context and complexity on responses made to attribute-based stated preference questions.

Although we were unable to recover statistically identical preference parameters using our split-sample design and different response formats, highly similar preferences were recovered, allowing some general conclusions to be made. First, the general public in Maine preferred a balance of timber harvest and natural area protection and they were willing to pay for an increase in the amount of forest land set aside from timber production relative to the base level. This result echoes the findings reported in Garrod and Willis (1996). Second, our results showed that clear cut timber felling greatly reduced conditional indirect utility, similar to findings reported in Hanley et al. (1998) and Boxall and MacNab (2000). Third, as an alternative to clear cutting, the public preferred a medium-intensity felling alternative relative to light-intensity harvests. This result may reflect public awareness of the practice of high-grading stands in which the best trees are selected for harvest, leaving genetically inferior trees for regeneration. Fourth, our results showed that the public prefers timber harvesting alternatives that leave standing dead trees after harvest (mimicking one aspect of old-growth forest structure) and that leave harvesting slash in the woods (which benefits soil productivity and provides habitat for small animals and insects).

The general public in Maine, as represented by our survey respondents, was willing to pay a considerable amount for timber harvesting practices that reduced the biological and amenity impacts on forest ecosystems. Willingness to pay for reduced-impact harvesting alternatives likely reflects the public's concern with a variety of goods and services associated with healthy forest ecosystems, including the provision of timber, recreational opportunities, wildlife habitat, and aesthetically pleasing views. We think that carefully conducted citizen surveys, such as those presented here, can help forest managers and policy makers identify management alternatives preferred by the public and that such information can add balance to public debates regarding forest policy.

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[1] In 1996, a Ban Clearcutting Referendum was placed on the ballot with a more moderate Forest Compact developed by the Governor. The Ban Clearcutting initiative and the Forest Compact were rejected by voters. The Forest Compact was again placed on the ballot in 1997 and was again defeated. Subsequently, the conservation community worked out a 4-point plan that would have (1) placed strict limits on the amount and size of clearcuts, (2) set science-based post-harvest stocking standards, (3) ensured that cutting does not exceed growth, and (4) imposed mandatory audits to ensure the protection of ecosystem integrity. The Maine legislature subsequently voted down the 4-point plan.

[2] For a good review of rating, ranking, and choice methods, see Louviere (1988).

[3] Randomness in an individual's utility function is attributable to variation in preference unobserved by the researcher as well as errors in perception, discrimination, and optimization by the consumer (McFadden 1986).

[4] The cumulative distribution of the EV1 is: $F(\varepsilon) = \exp[-e^{-\mu(\varepsilon-\eta)}]$ (where η is a location parameter and μ is a positive scale parameter).

[5] The IIA property can be tested using the standard Hausman-McFadden test (1984). If the IIA property is violated, other modeling approaches are available, such as the nested form of MNL.

[6] Louviere et al. (2000, pp. 235-236) show that as variance approaches infinity, scale approaches zero, and the MNL model predicts equal choice probability for all alternatives due to a lack of discrimination between alternatives. Conversely, as variance approaches zero and scale approaches infinity, the MNL model perfectly discriminates between alternatives, and the logit function behaves as a step function.

[7] The scale parameter can also be estimated using a nested logit model (see Louviere et al. 2000). The main advantage of the full information maximum likelihood method is that a standard error for the scale parameter is estimated. Scale can also be parameterized with individual or design characteristics.

[8] As noted by Ben-Akiva et al. (1992), steps 1 through 6 can also be used to test the stability of parameter estimates from exploded ranks.

[9] For a description of effects coding, see Holmes and Adamowicz (2003) or Louviere et al. (2000).

[10] Tax prices used were \$1, \$10, \$20, \$40, \$80, \$120, \$140, \$160, \$180, \$200, \$400, \$800, and \$1600.

[11] The option of not choosing (or not providing ranks for) any of the alternatives was included in a later question where people were asked whether or not they would vote for each of the alternatives if they were presented in a referendum.

[12] McFadden's R^2 is computed as $(1 - L(\beta)/L(0))$, where $L(\beta)$ is the likelihood value computed using the full set of parameter estimates, and L(0) is computed using an intercept only.

[13] The lack of significance of riparian buffers may reflect a relatively high standard for the base level (250-R buffer) and indifference between the base level and a more stringent standard. Lack of significance for road density may indicate ambivalence across the sample between the gain in access due to greater road density and the loss of ecosystem services.

[14] The parameter value for the omitted attribute level can be computed for effects coded variables. The value of the parameter for the L^{th} level of an attribute is the sum $b_1(-1) + b_2(-1) + \ldots + b_{L-1}(-1)$ where b_n is the parameter estimate on the n^{th} level $(n \neq L)$ of an effects coded variable.

[15] This result is consistent with results reported in Boyle et al. (2001).