Chapter 6

ATTRIBUTE-BASED METHODS

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1. INTRODUCTION

Stated preference methods of environmental valuation have been used by economists for decades where behavioral data have limitations. The contingent valuation method (Chapter 5) is the oldest stated preference approach, and hundreds of contingent valuation studies have been conducted. More recently, and especially over the last decade. a new class of stated preference methods has been developed, which we generically refer to as attribute-based methods (ABMs). As with contingent valuation, numerous ABM variants exist, employing, for example. different constructs for eliciting preferences. In this chapter, we describe the various ABMs currently used, explain how to construct an attribute-based experiment. and recommend methods for environmental valuation

The objective of an ABM stated preference study is to estimate economic values for a technically divisible set of attributes of an environmental good. Responses to survey questions regarding versions of an environmental good that vary in levels of its attributes can provide resource managers and policy makers with detailed information about public preferences for multiple states of the environment. The inclusion of price as an attribute permits a multi-dimensional valuation surface to be estimated for use in benefit-cost analysis. The focus on economic welfare and willingness to pay (WTP) distinguishes the environmental economists' use of ABMs from other applications of conjoint analysis.

ABMs can offer several advantages relative to other valuation methods:

- The experimental stimuli are under the control of the researcher, as opposed to the lack of control generally afforded by observing the real market place. This includes the introduction of new attributes and attributes associated with passive uses that cannot be observed in the marketplace.
  The use of statistical design theory yields greater statistical efficiency and eliminates collinearity between explanatory variables.
- A multi-dimensional response surface is modeled that provides a richer description of preferences than can he obtained by the valuation of single "with versus without" scenarios. This richness enhances the application of ABMs to managerial decision making.
- Salient attributes of the valuation problem are clearly circumscribed. Attributes are traded off in the process of value elicitation so that a reduction in one attribute may be compensated by an increase in another attribute.

Modern applications of ABMs are based on theoretical and empirical foundations spanning several decades. To convey a sense of the richness of ABMs as developed in a variety of academic disciplines, this chapter provides an overview of the conceptual foundations that Support contemporary applications of ABMs. After providing a historical perspective, we describe the basic steps for conducting an attribute-based experiment Then we expand upon a set of selected topics in experimental design that are important to understand when developing an attribute-based experiment. Next, we review the three most popular- response formats for conducting ABMs: ratings, rankings. and choice. An application of a choice experiment to a forestry issue is presented to illustrate the implementation and interpretation of a choice-based model. We then provide descriptions of models that relax the standard assumptions, which are the subject of much current research We end with an overview of the future directions of ABM research.

2. AN INTERPRETIVE HISTORY

The origins of currently popular ABMs are found in various social science disciplines. This creative merging of disciplines has generated some confusion in terminology and classification. By presenting an interpretive overview of the literature. we hope to clarify the main concepts needed to apply ABMs to non-market valuation, and to distinguish between non-market valuation and other applications of ABMs.

Within economics, the conceptual foundation for ABMs finds its source in the "hedonic" method that views the demand for goods as derived from the demand for attributes. This approach can be traced to Court (1939) who used hedonic regressions to study the demand for automobiles, and Griliches (1961) who used hedonic regressions in the construction of hedonic price indices. The hedonic model was put on a firm theoretical foundation by Lancaster (1966) using household production theory. Although theories of information processing in the judgment and decision making literature in psychology (Hammond 1955; Anderson 1970) have also included discussions of how consumers evaluate characteristics of items and use these evaluations in choosing between items, Lancaster's theory of consumer demand provides the basic conceptual structure that underlies economic applications of ABMs.

At the same time that Lancaster was writing about consumer demand being driven by commodity attributes, a new measurement technique in mathematical psychology was articulated for decomposing overall judgments regarding a set ofcomplex alternatives into the sum of weights on attributes of the alternatives (Luce and Tukey 1964). This method, known as "conjoint measurement", was rapidly embraced by marketing researchers who recognized the value of information about the relative importance of commodity attributes in thedesign of new products (Green and Rao 1971; Green and Wind 1975). This new marketing research method became generally known as "conjoint analysis".[1]

Many commercial applications for conjoint analysis were soon found, particularly the predictinn of mar-hct share for new products (Cattin and Wittink 1982). The typical procedure would ask respondents to rate the attractiveness of a set of products and then model the preferences of each respondent (see Section 9).[2] Predicted utilities for competing products would then be computed for each individual and entered into a choice simulator to estimate the market share, computed over the sample, for each competing product (e.g., see Green et al. 1981).[3] This approach emphasized the importance ofcapturing individual-level preference heterogeneity as a key element in predicting marhet share.

Despite these advances, two primary concerns arose regarding the typical conjoint procedure. First, it was not clear that the information contained in rating data was the same as the information contained in choice data. Second, implementation of choice simulators was cumbersome and often confusing to managers who used the predictions of market share models.

A simpler, more direct approach to predicting choices in the market place was provided by discrete choice theory, particularly as formulated for economic analysis by McFadden (1973). The conceptual foundation for McFadden's analysis of economic choice lay in Thurstone's (1927) idea of random utility (discussed in greater detail in Section 6). By positing that individuals make choices that maximize their utility, and that utility is "subject to the vagaries of whim and perception". McFadden (1986, p. 278) was able to place choice theory on a strong economic foundation that included a richness ofbehavior not found in standard Hicks-Samuelson theory." In addition, starting with Luce's choice axiom (1959). as linked to the random utility model by Marschak (1960), McFadden developed an econometric model that combined hedonic analysis of alternatives and random utility maximization.[5] J-his model is known as the multinomial logit (conditional logit) model.

A further advance identified by McFadden and others is the linkage between random utility models and welfare economics. The utility function in random utility models is actually a conditional indirect utility function (conditional on the choice of the alternative). Thus. including price. or more formally income minus price, as an attribute in the conditional indirect utility function allows one to assess economic welfare measures (e.g., compensating variation: see Small and Rosen, 1981). 'This differentiates random utility applications of ABMs in economics from other non-economic applications since economists are often interested in welfare measures and are always cognizant of the need to be consistent with theory.

The conceptual richness of random utility theory, and the practical advantages of the multinomial logit (MNL) model. were embraced by marketing researchers who promoted the use of MNL to analyze aggregate marketing data (Louviere and Woodworth 1983; Louviere and Hensher 1983; Louviere 1988a). The random utility model also found wide application in modeling transportation demand (a comprehensive treatment is provided in Ben-Akiva and Lerrnan 1985).[6] Initial work using the MNL model was based on the analysis of aggregate data but recent methodological developments have. focused on understanding sources of individual preference heterogeneity in random utility models (see Section 12), reminiscent of the focus on individual-level modeling used in early applications of conjoint analysis.

In addition to rating and choice response formats, another variant of ABMs developed in marketing and transportation research was to ask respondents to rank bundles of attributes from most preferred to least preferred Ranking data have the advantage of not requiring the assumption of cardinal utility that was typically relied on to analyze rating data. A popular interpretation of ranking data is based on a random utility model of choice behavior in which respondents make a sequence of choices. and the number of alternatives in the choice set decreases as ranking depth increases (this model is described in greater detail in Section 8). Thus, ranking data could be analyzed using a special form of the MNL model (Beggs.Car-dell and Hausman 198 l ; Chapman and Staelin 1982).

The ability to decompose values of environmental programs into implicit values associated withparticular attributes of those programs has made ABMs attractive to environmental economists. Although the three major response formats (rating, ranking and choice) have all been used by economists. the first application of ABMs to environmental valuation that we are aware of was Rae's (1983) work using rankings to value visibility impairments at Mesa Verde and Great Smoky Mountains National Parks. However, **only** a weak empirical association between rankings and visibility was observed. Stronger empirical support for ranking models was later provided by Smith and Desvousges (1986) who evaluated water quality in the Monongahela River, and Lareau and Rae (1989) who evaluated WTP for diesel odor reductions. After a hiatus of nearly a decade. a number of recent studies have been conducted using the ranking model for non-market valuation of environmental amenities (Garrod and Willis 1996 and 1998: Foster and Mourato 2000; Layton 2000; Morrison and Boyle 200 l).

ABMs using rating data to value environmental quality began growing in popularity during the earl! 1990's. Mackenzie (1993) showed how rating data could be converted to rank and choice data. Gan **and** Luzar (1993) used ratings to model waterfowl hunting site decisions. Roe, Boyle, and Teisl (1996) showed how compensating variation can be estimated from rating data.

During the same period that rating models for environmental valuation were being developed, a number of studies were reported using random utility models ofchoice. Adamowicz. Louviere. and Williams (1994) recognized that random utility theory provides a common conceptual foundation for a class of stated preference and revealed preference models and demonstrated how revealed and stated preference data can be combined.' At present, choice-based ABMs are receiving the most attention.

3. STEPS IN CONDUCTING AN ATTRIBUTE-BASED EXPERIMENT

Implementation of an attribute-based experiment should follow the seven steps outlined in Table 1 (Adamowicz, Louviere, and Swait 1998; Louviere, Hensher, and Swait 2000). Each step is briefly described below.

Table 1 Steps in an Attributed-Based Experiment

1	Characterize the decision problem
2	Identify and describe the attributes
3	Develop an experimental design
4	Develop the questionnaire
5	Collect data
6	Estimate model
7	Interpret results for policy analysis or decision support

The initial step is to clearly identify the economic and environmental problem. This requires thinking about two key issues: (1) the geographic and temporal scope of the change in environmental quality, and (2) the types of values that are associated with changes in environmental quality. Regarding the first key issue, several questions should be considered: Are changes in environmental quality limited to a single site or will they impact multiple sites? Are there any possible spill-avers between changes at one site and changes at other sites? Will changes be implemented instantaneously or will they take time to be fully realized?

'The second key issue focuses attention on the types of values that are affected by changes in environmental quality. This requires consideration of the following questions: Who will benefit from changes in environmental quality? Will passive uses be affected? And, if the changes in environmental quality affect use value, what is the behavior that best captures this value'?

Consider, for example, valuation of the benefits from improving a specific beach recreation site. The relevant values would be associated with changes in various beach attributes (such as water clarity, showers, picnic areas, and so forth). The relevant behavior to model is beach choice (from a set of beaches) and the frequency of trips. And. if changes in environmental quality also impact people who do not use the bench. passive use values need to be considered as well.

Once the decision problem is specified, the relevant attributesare identified and characterized (step 2). Continuing with the beach choice example, the researcher must identify the most important attributes ofbeaches that influence decisions regarding which site(s) to visit. Focus groups, or structured conversations with people who are broadly representative of the population that will be sampled. are used to identify the important attributes. For example, we might ask members of a focus group "How would you describe an excellent beach. or a poor beach'?" or "What things do you consider when choosing a beach to visit?" At this stage, it is also necessary to decide how many attributes to include in the experiment as well as the particular levels that each attribute can take. How people respond to highly complex survey questions is unknown (e.g.. see Mazzotta and Opaluch 1995; Swait and Adamowicz 2001a and 2001b). so it is good to keep the set of attributes as simple as possible.

Steps 1 and 2 are critically important to the successful application of ABMs but these steps are often not given the due consideration that they require. If the researcher either inappropriately frames the choice problem or omits important attributes. the entire experiment isjeopardized. We encourage practitioners to spend significant time and effort in scoping the problem. using focus groups and pre-tests. and making sure that the choice context and scenario descriptions are well developed.

After attributes and levels have been determined, in step 3 experimental design procedures are used to construct the alternatives that will be presented to the respondents. As mentioned above. the objective of an ABM stated preference study is to identify WTP for the attributes of an environmental good WTP values are constructed from econometric estimates of the preference or taste parameters (coefficients of a utility model). The scenarios presented to respondents must provide sufficient variation over the attributes to allow the researcher to identify the taste parameters. In most cases. presenting all combinations of attributes and levels will be impossible. Thus, experimental design procedures must be used to identify subsets of the possible combinations of attributes and levels that will "best" identify the attribute preferences. Economists tend not to receive formal training in experimental design because they seldom construct controlled experiments. Therefore. we present Section 4 as a primer to this important topic.

In step 4 the questionnaire is developed. All ABMs involve surveys of some sort. As with other stated preference methods. various modes of administration are available:

- mail-out. mail-back surveys
- telephone recruitment, mail-out, mail-back surveys
- telephone recruitment, mail-out: telephone surveys
- computer-assisted surveys at centralized facilities
- intercept surveys, which may be paper-and-pencil or computer assisted
- internet-based surveys.

To date. the performance characteristics associated with various administration modes (in terms of overall response rate and item non-response) are not known. Thus. selection of the mode of administration is usually based on pragmatic concerns such as geographic specificity of the target population and budget limitations.

Various methods can be used to communicate information about the attributes of the valuation problem. In addition to verbal descriptions. graphic displays such as maps. photographs, and line drawings should be considered. As in any survey-based research. pi-e-testing of the questionnaire is absolutely necessary to assure that respondents clearly understand the information being communicated (see Chapter 3 for more detail on survey methods).

In step 5. the data are collected using the best survey practices (e.g., Dillman 1978). Chapter 5 outlines a number of issues in data collection for contingent valuarion studies that apply as well to the implementation of ABMs.

In step 6. the taste parameters in the utility model are estimated econometrically The choice of econometric method depends on the response format (choice. ranking, or rating) and on a variety of econometric considerations. as discussed in Sections 7 through 9.

Finally, the results are interpreted for policy analysis and decision support. ABM applications are targeted to generating welfare measur-es, predictions of behavior, or both These models are used to simulate outcomes that can be used in policy analysis or as components of decision-support tools. Estimation of welfare measur-es is described in Section 10.

4. EXPERIMENTAL, DESIGN

A strength of attribute-based experiments is that they allow the researcher to manipulate the set of explanatory variables associated with the attributes of the environmental valuation problem. However, without a proper understanding ofexperimental design. this asset can become a liability. The design determines both the types ofeffects that can be identified in the data and the interpretation of those effects. Without a proper design. an improperly specified model with biased parameter estimates and collinear variables may result.

Designed experiments are widely used in biological, physical, and behavioral sciences but are not as familiar to economists, who have historically favored the analysis of secondary data generated by social processes. A designed experiment involves the manipulation of independent variables. called *factors*, over pre-specified factor levels. Factors that represent features or characteristics of a consumer good or service are typically referred to as *attributes*.

4.1 Factorial Designs

A factorial design combines every level of each attribute with every level of all other attributes (e.g., Cochrane and Cox 1957; Snedecor and Cochrane 1974; Winer 1971). Each combination of attribute levels is called an *alternative*, *profile*, or *treatment combination*. We use these terms interchangeably (although profile is more commonly used in conjoint analysis. since combinations ofattributes are often examined one-at-a-time and, thus, arc not truly “alternatives”). As you can anticipate. a problem of the full factorial design is that a large number of alternatives are generated as the numbers of attributes and levels are increased.

To set the stage, consider a state parks and recreation agency that is evaluating various designs for a new campground. Suppose that agency managers need to decide whether or not to build picnic shelters. playgrounds, and showers at the new campground. Each of the three "facility" attributes takes two levels ("build" or "do not build"). Thus. there are 2’ possible combinations of facilities. This is referred to as an L^n design, where L refer to the number of levels and n refers to the number of attributes. in this case. the full factorial design includes 8 possible combinations of attributes.

The primary advantage of a factorial design is that all "main" and "interaction" effects are independent (orthogonal) and can be identified. A "main effect" is the difference between the average (mean) response to each attribute level and the overall average (or "grand mean"). In multiple regression, main effects are represented by parameter estimates for the attribute levels and the grand mean is the *intercept*. An "interaction effect" occur-s if the response to the level of one attribute is affected by the level ofanother attribute. Interaction effects are represented by the parameter estimates for the interact ion (cross-product) of two (or more) variables in a multiple regression model.

Interaction effects are important in economics because they represent the concepts of *complementarity* and *substitutability*. *In* the example above, the average consumer may respond more favorably to a new campground with picnic shelters if playgrounds are also included in the campground description'. If so. picnic shelters and playgrounds are complements. A less than full factorial design may fail to detect the interaction between picnic shelters and playgrounds and could possibly confound the interaction with one of the main effects. The reasoning behind this result follows.

4.2 Fractional Factorial Designs

Fractional designs reduce the number of profiles or alternatives included in a design to reduce the cognitive burden faced by respondents. However, information is potentially lost when fractional designs are used. Po understand why fractional designs typically omit information on interactions among attributes. and the potential impact of fractional designson parameter estimates. an understanding of *aliasing* (or *confounding*) is required.

The alias of an included effect consists of the correlated omitted effects in a fractional factorial design Attribute codes that are completely uncorrelated are useful for identifying correlated effects. Orthogonal polynomial codes are used for this purpose. Two-level variables are represented by l and + l rather than 0 and +1 used for dummy variables (for details see Louviere 1988a; Louviere. Hensher. and Swait 2000).

The concept of aliasing can be illustrated with a one-half fraction of a 2^3 design. Returning to our campground example. let A1 represent "picnic shelters", A2 represent "showers", and A3 represent "playgrounds". Table 2 shows the main and interaction effects for the full-factorial and two ½ fractions of the full design. The main effects in the full-factdrial are specified using all possible combinations of attributes. Interaction effects are defined by multiplying columns (cross-products) of the orthogonal polynomial codes for each attribute.' Now, note that in the first one-half fraction of the full factorial (combinations 1 through 4), the vector of 2-way interactions A1A2 [+1, -1, -1, +1] is exactly the same as the vector of main effects for A3. Thus, A1A2 is perfectly collinear (confounded) with A3 (A3 is an alias for the A1A2 interaction). If only the first four attribute combinations in Table 2 were used for a 2^2 factorial, and a regression analysis showed that the parameter estimate on A3 was significantly different from zero, we could not be certain whether playgrounds were significant, the combination of picnic shelters and showers was significant, or both. The parameter estimate on A3 is unbiased only if the A1A2 interaction equals zero.

Table 2 Orthogonal codes showing two ½ fractions of a 2^3 factorial design

	Main effects			*2-way interactions*			*3-way interactions*
Profile	Picnic shelter A1	Showers A2	Playground A3	A1 A2	A1 A3	A2 A3	A1 A2 A3
		First ½ fraction					
1	-1	-1	+1	+1	-1	-1	+1
2	1	+1	-1	-1	+1	-1	+1
3	+1	-1	-1	-1	1	+1	+1
4	+1	+1	+1	+1	+1	+1	+1
		Second ½ fraction					
5	-1	-1	-1	+1	+1	+1	-1
6	1	+1	+1	-1	-1	+1	-1
7	+1	-1	+1	-1	+1	-1	1
8	+1	+1	-1	+1	-1	-1	-1

We also note that the 3-way interactions in the first ½ fraction in Table 2 always take the value "+1". Thus, the intercept in a regression model is perfectly collinear with the three-way interaction A1A2A3.[9]

From a practical perspective, it is generally not known a *priori* which attributes are complements or substitutes. To shed some light on the issue, first-order (2-way) interactions can be evaluated during the focus group stage of survey development. If focus group participants indicate that the attractiveness of a particular attribute depends in part on the level of other attributes, then "main effects plus selected interaction" designs can be constructed (Carmone and Green 1981). Higher order interaction effects typically have little explanatory power and probably can be ignored.

If focus groups and pre-tests reveal that interactions can be safely omitted. design catalogues are available for orthogonal fractional factorial main effects plans (e.g.. Adelman 1962; Hahn and Shapiro 1966; McLean and Anderson 1984). However, if complements and substitutes are important elements of preferences for the environmental good(s) under consideration, specialized software that supports "main effects plus interactions" plans can be used.

4.3 Randomized Designs

In addition to factorial and fractional factorial designs, other strategies are available for designedexperiments." In principle, random samplingofattribute levels from the full factorial design space will maintain orthogonality of the design. Of course. this result is valid only for large samples. For small samples. random sampling may induce unwanted correlation among attributes. For example. consider a design for 5 attributes each with 4 levels. The full factorial for a 4^5 design yields 1024 possible profiles. Consider constructing a 1/32 fraction design by random sampling of the design space until 32 profiles are selected. Because 32 random profiles represent a small fraction of the design space, the randomly generated profiles could be clustered by the "luck of the draw". If all respondents are shown profiles from the same sample of profiles, sampling a small proportion of the design space may result in a set of correlated attributes, which reduces the efficiency of the design.

The ability of computers to randornly sample and store large amounts of data offers a second random sampling technique. the completely randomized design, wherein a randomly sampled profile is generated for each respondent in the sample. If, for example, a researcher anticipates that 1,000 people will respond to an ABM questionnaire, random assignment of attribute levels to profiles for each respondent would nearly span the entire design space in a 4^5 full factorial. Of course, it is not guaranteed that every randomly generated profile will be unique. However, if each respondent is presented with 2 or more profiles. as is usual practice in an attribute-based experiment, then it is likely that the entire design space will be sampled by randomly generated profiles.

After randomly generating profiles, it is a good idea to evaluate the experimental design by examining the correlation matrix of main effects to assure that the design is orthogonal. In addition, the correlation matrix of main effects and 2-way interaction effects should be examined for evidence of confounding.

4.4 Correlated Attributes

Attributes encountered in environmental valuation problems may be highly correlated by natural processes and, thus, they are not intrinsically separable. If two correlated attributes were treated as independent in a valuation experiment, respondents might become confused, reject the scenario, and fail to answer the question. Although some empirical studies indicate that treating correlated attributes as independent factors does not cause serious problems (Huber and McCann 1982: Moore and Holbrook 1990), it is safest to use only feasible combinations of attributes. In general, the problem of correlated attributes is best solved by selecting attributes that represent separable dimensions of the valuation problem.

4.5 Designs for Choice Experiments

When the rating response format is used in an attribute-based experiment, the efficiency of an experimental design is maintained by construct ing profiles that are independent (uncorrelated) over the iterations (sequence of rating tasks) of the experiment. However, the design of a choice experiment is complicated by requiring respondents to compare two or more alternatives simultaneously. Maximum design efficiency requires selection of attribute levels that are independent of one another both within and between alternatives. This results in a L”“‘ factorial design. where m refers to the number- of designed (non-status quo) alternatives in each choice set presented to respondents.

Let‘s revisit the campground design problern where the full factorial design is represented by 2’ (L,“) possible combinations of attributes. If a rating scale response format were used, then the full factorial for this problem would be represented by 8 profiles (as in Table 2). It is possible that people could meaningfully respond to all profiles in the factorial design, and you could test hypotheses about all main and interaction effects. However, if a two-alternative choice response format were used. the full factorial would include 2’ x 2’ (L^n x L^n = L^{2n}, where m = 2) combinations of attribute levels and choice alternatives.

or 64 (8 x 8) possible pairs of profiles (choice sets). Choice formats with more alternatives would clearly require even larger designs. Although there is no definitive number ofchoices that people can respond to without being fatigued, most researchers use no more than 8 or sometimes 16 choice sets. A design with 64 choice sets would be too large a design for people to respond to. A main effects design could be selected from this collective factorial if one assumed that there were no interaction effects. An example choice set is shown in Table 3.

Table 3 A campground choice set taken from a 2^6 (2' * 2') factorial

Attribute	Alternative	
	Camp site A	Camp site B
Showers	No	Yes
Play grounds	Yes	No
Picnic shelters	NO	Yes
I would choose please check one box	☐	cl

In actuality, the choice experiment presented above would not be very useful to economists because no price variable (distance) is included and because choosing neither of the alternatives (opting out) is not allowed. Let us expand the example to include a 4^{th} attribute, distance. that also has two levels (Table 4). Now the campground problem contains 4 two-level attributes in each alternative and the overall problem can be represented by a 2' * 2' or 2^8 main effects plan.

What is the smallest main effects plan (design with no interaction effects) that could be selected for this campground choice problem? This is determined by first evaluating the number of degrees of freedom needed to estimate the entire set of main effects (Louviere, Hensher, and Swait 2000). In our example with L=2 and n=4, there are 8 main effects (L x n). and each main effect has I (or L - 1) degree(s) of freedom T-here are 8 main effects because each level of each attribute constitutes a main effect. Thus, there are a total of $(L \times n) \times (L - 1) = 8$ degrees of freedom plus one degree of freedom for the equation intercept. Next, the number oforthogonal choice sets in the fractional factorial must exceed the number of degrees of freedom. An orthogonal main effects $2^{(8-4)}$ fraction of the 2^8 factorial satisfies this requirement. Thus, the smallest orthogonal main effects plan for this example requires 16 choice sets." The nttrnber of choice sets offered defines the number of iterations or replications of the choice experiment.

Table 3 A campground choice set taken from a 2^8 factorial

Attribute	Alternative		
	Camp site A	Camp site B	Stay at home. I would not choose either camp site A or B and would stay at home instead
Distance	50 miles	100 miles	
Showers	No	Yes	
Play grounds	Yes	No	
Picnic shelters	No	Yes	
I would choose please check one box	☐	☐	cl

Suppose that in the campground choice problem it was decided that 16 choice sets were too many for people to reasonably consider. In this case, choice sets could be assigned to "blocks" (independent subsets of the overall design) and each respondent assigned randomly to a particular block. Two methods can be used for blocking. The first method is to list the choice sets in random order and then subdivide the list to obtain blocks of "reasonable" size. For example, 16 choice sets may be reordered and separated into 4 blocks of 4 choice sets each. With the second method. blocks are considered another attribute in the experimental design. where the number of levels is represented by the number of desired blocks. Including blocks as attributes in an orthogonal·design assures that every level of all attributes will be present in every block (Adamowicz, Louviere, and Swait 1998).

When considering the number of choice alternatives to present in a choice set, one attractive option is the binary choice experiment. This is simply the ABM version of the binary (or dichotomous) choice model used in contingent valuation. A binary choice experiment can be posed as a referendum ("Would *YOU* vote for a given profile'?") given a certain specification of environmental attributes. The binary choice experiment reduces the full factorial design in a choice experiment from L^{mn} to L" because in this case m = I Econometric models are widely available for analyzing binary choice experiments that are not generally available for multinomial choice experiments."

Another issue to consider when designing choice alternatives is whether choice alternatives should be generic or "branded". A branded alternative in the camping example would include catnp site natnes as labels for the alternatives (such as "Jasper National Park"), and ask respondents to consider choices from the labeled alternatives, with the attributes and levels as specified However, it is important to recognize that the brand name might be highly collinear with attributes otnitted from the choice problem If brand name is collinear with omitted attributes and is not included in the model specification, then parameter estimates are affected by omitted variable bias. Fortunately, this can be sitnply handled by including alternative-specific constants in the econometric specification to account for the utility associated with the alternative that is independent of the attributes (see Section 5).

In the design of a choice experiment, a common recommendation (e.g., Louviere, Hensher, and Swait, 2000) is to mimic an actual market situation by including a constant opt-out option (e.g., "I would not **choose** any of the available alternatives"). Continuing with the catnpground selection problem shown in Table 3, a typical question would ask the respondent to choose among camp site A, catnp site B. or the option to stay at home. In this case. adding the choice to not go camping would allow for the possibility that when individuals are presented with camping alternatives that are not satisfactory to them. they will respond by choosing not to go catnping. Without the stay-at-home option, respondents are required to choose a camping alternative. even in cases where they would never choose to go catnping under the specified conditions. In practice, the opt-out alternative is not modeled in a sophisticated fashion (for a discussion of inclusion of the opt-out alternative see Lou\-iere. Hensher, and Swait, 2000, and the discussion of alternative-specific constants in the section itntnediately following). If an "opt-out" alternative is not presented, the choice provides information on preferences, conditional on choosing one of the alternatives, but it does not provide information on whether the individual would choose one of the alternatives or not. We believe that choice scenarios should include opt-out options because in most real world choice situations, individuals are not in a situation of "forced choice" and they have the option to choose not to choose. A more important issue for debate may be the form of the opt-out option and the econometric modeling of this option."

5. ATTRIBUTE CODING SCHEMES

Coding quantitative attributes. such as travel distance. is straightforward because the attribute level is a quantity. However, qualitative attributes pose a problem Of course. dummy variables can be defined for L 1 qualitative attribute levels in the usual manner and, for ease of interpretation. the status quo level can be designated as the "omitted" level so that parameter estimates on included levels represent changes from the status quo. The problem. however. is that when dummy variables are used to code attribute levels, the attribute level associated with the omitted category is perfectly collinear with the intercept in a regression model. 'Thus. no information is recovered about preferences regarding the omitted level.

This limitation can be overcome by using effects codes. Because effects codes are uncorrelated with the intercept, the values of omitted levels for- each attribute **can** be estimated (Louviere, Hensher, and Swait 2000).

Effects codes are created as follows. Begin by creating an effects-coded variable, EC_1, for the first attribute using 3 criteria:

1. If the profile contains the first level of the attribute. set $EC_1 = 1$
2. If the profile contains the L^{th} level of the attribute, set $EC_1 = 1$.
3. If neither step 1 or 2 apply, set $EC_1 = 0$.

If an attribute has two levels. we only need to create one effects-coded variable using the preceding 3 criteria for that attribute. However. if an attribute has three levels. we continue the coding process by creating a second effects coded variable, EC_2, for that attribute using 3 additional criteria:

4. If the profile contains the second level of the attribute. set $EC_2 = 1$.
5. If the profile contains the L^{th} level of the attribute, set $EC_2 = -1$.
6. If neither step 4 or 5 apply, set $EC_2 = 0$.

if an attribute has tnore than three levels, we continue creating effects codes in this manner until L- 1 effects codes are created for each L- level attribute.

Using this coding scheme, the parameter value for the omitted attribute level can be simply computed. For example, the value of the parameter for the L^{th}-level of an attribute is the sum $b_1(-1) + b_2(-1) + \; + b_{L-1}(-1)$, where b_n is the parameter estimate on the n^{th} level $(n \neq L)$ of an effects coded variable. An example of effects coding is presented in Section 11 below

Jfnn attribute-based experiment contains branded alternatives or an opt- out option (e.g., stay at home option in a recreation choice experiment). it is necessary to use dummy variables known as *alternative-specific constants* (ASCs). As previously suggested. people might respond in some degree to a brand name independent of the attribute levels. ASCs identify the utility of branded alternatives not accounted for by the attributes of those alternatives. It is also essential to create an ASC for the opt out option to capture the utility associated with that option. Since the opt-out alternative usually has no attributes, an ASC is necessary to model this alternative's utility. If there are K alternatives in the choice set. then (K 1) ASCs are included in the econometric specification.

6. RANDOM UTILITY

Models used to implement an attribute-based experiment for environmental valuation should be based on an explicit utility theory. Much of the recent work in environmental valuation is based on random utility maximization (RUM).[14] The RUM model assumes that utility is the sum of systematic (v) **anti** random components:

$$(1) \qquad U_j = v(x_j, p_j; \beta) + \varepsilon_j$$

where U_j is the true *but unobservable indirect utility* associated with profile *j*, x_j is a vector of attributes associated with profile *j*, p_j is the cost of profile *j*, β is a vector of preference parameters. and ε_j is a random error term with zero mean.[15] Choice behavior is assumed to be deterministic (without error) from the perspective of the individual, hut stochastic from the perspective of the researcher because the researcher does not observe everything about the individual. Thus the error term in the random utility expression reflects researcher uncertainty about the choice. It is usually assumed that **utility** is linear-in-parameters:

$$(2) \qquad U_j = \sum_{k=1}^{I} \beta_k x_{jk} + \beta_p p_j + \varepsilon_j$$

where β_k is the preference parameter associated with attribute *k*, x_{jk} is attribute *k* in profile *j*, and β_p is the parameter on profile cost. However, if interactions are included in the experimental design, a utility function that includes interactions (quadratic terms) can be specified as:

$$(3) \qquad U_j = \sum_{k=1}^{I} \beta_k x_{jk} + \beta_p p_j + \sum_{m=1}^{I} \sum_{k=1}^{I} \beta_{km} x_{jk} x_{jm} + \varepsilon_j$$

where β_{km} is a vector of preference parameters for interactions between attributes *k* and *m* in profile/. and x_{jk} and x_{jm} are attributes *k* and *m* in profile *j*. Equation (3) includes all possible substitute/complementary relations between attributes. In practice, only a subset of all possible attribute interactions would likely be specified in an attribute-based model.

By differentiating equation *(2)*. it is seen that parameter estimates (p's) in an additively separable linear utility model represent marginal utilities: $\beta_k = \partial U/\partial x_k$. 'The parameter estimate on profile cost. β_p, has a special interpretation. Because an increase in profile price decreases income, β_p registers the change in utility associated with a marginal decrease in income. Thus, the negative of the parameter estimate on profile cost. β_p. is interpreted as the marginal utility of money.

The marginal rates of substitution between any two attributes *k* and *m* is easily computed as the ratio of two parameter estimates ($MRS_{km} = \beta_k / \beta_m$). The marginal value (implicit price) of attribute *k* is computed as the ratio $\beta_k/\beta_p = (\partial U/\partial x_k)/(\partial U/\partial p_j)$. Differentiation of equation (3) shows that the marginal utility of attribute x_k in a quadratic utility function depends on the level of x_m: $\partial U/\partial x_k = \beta_k + \beta_{km} x_m$.

7. CHOICE

RUM provides the theoretical foundation for a class of empirical models based on consumer choices between competing alternatives. The choice problem asks respondents to choose the most preferred alternative from a choice set. This response format mimics actual market behavior, such as choosing a brand of cereal from among brands with different attributes. The choice format focuses the consumer's attention on the tradeoffs between attributes that are implicit in making a choice. Model estimates are based on utility differences across the alternatives contained in choice sets.

The stochastic term in the random utility function shown in equation (1) allows probabilistic statements to be made about choice behavior. The probability that a consumer will choose alternative i from a choice set containing competing alternatives can be expressed as:

$$(4) \qquad P(i|C) = P(U_i > U_j) = P(v_i + \varepsilon_i > v_j + \varepsilon_j), \forall j \in C$$

where C contains all of the alternatives in the choice set. Different probabilistic choice models can be derived depending on the specific assumptions that are made about the distribution of the random error term. If errors are assumed to be distributed according to a bivariate normal distribution, a binary probit model can be specified (Thurstone 1927) which can be generalized to the multivariate case via a multinomial probit model.[16] A type I extreme value (Gumbel) distribution yields the conditional or multinomial logit (MNL) model (McFadden 1974). A generalized extreme value distribution gives rise to the nested MNL model (McFadden 1981).

The standard assumption in using RUM has been that errors are independently and identically distributed (IID) following a type I extreme value distribution. However, the associated MNL model imposes the restrictions that: (1) preference structure is homogeneous over respondents (this assumption is relaxed in Section 12.1 below), (2) choices conform to the Independence from Irrelevant Alternatives (IIA) assumption[17] (this assumption is relaxed in Section 12.2 below), and (3) all errors have the same scale parameter.[18]

Equation (3) can be rearranged to show that, in RUM, choices are made based on utility differences across alternatives:

$$(5) \qquad P(i|C) = P(v_i - v_j > \varepsilon_j - \varepsilon_i), \forall j \in C.$$

Thus, any variable that remains the same across profiles, such as respondent income, drops out of the model. If errors are distributed as type I extreme value, the MNL model applies and the choice probability is written as:

$$(6) \qquad P(i|C) = \frac{\exp(\mu v_i)}{\sum_{j \in C} \exp(\mu v_j)}$$

where μ is the scale parameter." Given an additively separable specification of utility, and assuming that $\mu = 1$, the probability of choosing profile *i* from the set C is written as:

$$(7) \qquad P(i|C) = \frac{\exp(\sum_{k=1}^{I} \beta_k x_{ik} + \beta_p p_i)}{\sum_{j \in C} \exp(\beta_k x_{jk} + \beta_p p_j)}$$

If we let N represent the sample size and define

$$y_{in} = \begin{cases} 1 & \text{if respondent n chose profile i} \\ 0 & \text{otherwise} \end{cases}$$

then the likelihood function for the MNL model is:

$$(8) \qquad L = \prod_{n=1}^{N} \prod_{i \in C} P_n(i)^{y_{in}}$$

Substituting equation (7) into equation (8) and taking the natural logarithm, the MNL model is estimated by finding the values of the β's that maximize the log-likelihood function:

$$(9) \qquad \ln L = \sum_{n=1}^{N} \sum_{i \in C} y_{in} \left(\sum_{k=1}^{I} \beta_k x_{ikn} + \beta_p p_{in} - \ln \sum_{j \in C} \left(\sum_{k=1}^{I} \beta_k x_{jkn} + \beta_p p_{jn} \right) \right).$$

Choice based ABMs have been found to be useful for modeling use values (Adamouicz et al. 1997) and they were found to be useful in measuring passive use values as well (Adamowicz et al. 1998). Random utility models of choice have been used in a number of other studies including recreational site choice (Boxall et al. 1996) and policy/program evaluation (Viscusi et al. 1991; Opaluch et al. 1993: Hanley et al. 1998; Hanley, Wright. and Adamowicz **1998).**

8. RANKING

Contingent ranking questions ask respondents to rank a set of profiles from most preferred to feast preferred. This question format results in a series of responses from 1 to J for a set of J profiles. Ranking of responses ostensibly provides more information than a single choice because. in addition to the most preferred choice from a choice set. rankings provide information on preferences for all of the profiles included in the set. The standard interpretation of a ranking task views the ranking problem as a series of choices, and indeed a series of carefully constructed individual choice questions could provide the same information as a single ranking task.[20]

Analysis of ranking responses is typically conducted using random utility theory. Consider the problem of ranking profiles from the set $\{j, k, l, \ldots, J\}$. Marschak (1960) showed that a ranking problem can be modeled as a sequence of choices that. in turn, can be considered the product of independent probabilities:

$$\begin{aligned}(10) \quad & \Pr[j \text{ ranked 1st. } k \text{ ranked 2nd. } \ldots J \text{ ranked last}] = \\ & P(j|j,\ k,\ l,\ \ldots,\ J) \bullet P(k|k, l, \ldots, J) \bullet \ldots \bullet P(J-1|J-1,\ J)\ .\end{aligned}$$

Equation (IO) is based on the assumption that the respondent chooses the most preferred profile frorn the entire choice set. then the second ranked profile is chosen from the remaining choice set. and so forth. ffit is assumed that the J- 1 choices in a set of J profiles are independent, and if the additively separable linear utility model adequately represents the data. then the rank-ordered logit model (Beggs, Cardell, and Hausman 1981) describing the probability of a given ranking is written as a function of the probability of the utility of alternative j being greater than that of alternative k, the utility of k being greater than that of l, and so on:

$$(11) \qquad P(U_j > U_k > \ldots > U_J) = \prod_{j=1}^{J-1} \left(\frac{\exp[\mu(\sum_{k=1}^{I} \beta_k x_{jk} + \beta_p p_j)]}{\sum_{i=j}^{J} \exp[\mu(\sum_{k=1}^{I} \beta_k x_{ik} + \beta_p p_i)]} \right).$$

From a statistical perspective, the additional information provided by rankings should lead to smaller standard errors for parameter estimates or, equivalently, smaller sample sizes for a given level ofprecision (Hnusman and Ruud 1987). However, practical experience has shown that this is not always the case. Rankings are cognitively more demanding than a single choice, and respondents may become fatigued or confused as they proceed through the sequence of choices required in ranking. Consequently, parameter estimates may lack stability and "noise" may increase for lower ranks (Chapman and Staelin 1982; Ben-Akiva, Morikawa, and Shiroishi 1992: Holmes and Boyle 2002).

9. RATING

Rating scale questions require individuals to make judgments about the magnitude of' utility associated with profiles presented in an attribute-based experiment. It is implicitly assumed that judgments directly transform utility to the rating scale. Rating models can be simply estimated by regressing the vector of rating responses on the attribute levels included in each profile. Errors in rating models are often treated as additive nuisance parameters rather than having a structural interpretation as in RUM models.

Rating data are most often assumed to contain information on ordinal, not cardinal. preferences. An ordinal interpretation of rating data only requires, for example. that a response of *4* on a rating scale represents a higher intensity of preference than a *3*, but does not necessarily represent the same cardinal difference as a score of 2 relative to a score of *1*. Taking this view of rating data, it is appropriate to use an ordered probit or or-dered logit model" although many analysts employ ordinary least squaws procedures that can be implemented easily with rating data.

The use of ratings is appealing because of the simplicity of the econometric analysis and the ease with which respondents can answer rating questions. However. problems arise in using such an approach First. ratings must be adjusted so that a common metric is used across individuals (Torgerson 1958; Mackenzie 1993: Roe. Boyle, and Teisl 1996: Holmes et al. 1998). Second. a status quo or base situation (current choice) must be evaluated using the rating to judge whether an individual would rate a new alter-native higher than the status quo or base situation (which would imply choice of the alternative over the current situation) (Roe, Boyle, and Teisl 1996). Respondents may suggest that alternatives have equal ratings (ties), which presents problems when one is attempting to estimate ordinal econometric models and predict demand behavior. Decisions to include or exclude ties can effect parameter estimates (Boyle et al. 2001). Most of these challenges can be addressed using econometric procedures or by restructuring the data.

However, despite potential econometric "fixes" to rating data, we do not recommend their use for environmental valuation. Choice or ranking methods provide information on choice directly and do not require such econometric and data restructuring steps. Rating scales do not have a natural analogue in actual markets. Economic theory, in its most basic form, involves the prefer-ence of one object over another. Thus, choice methods correspond most dir-ectly with such a theory and form the most direct method of eliciting preference information. While ratings data may be used to develop welfare measures, choices or rankings are more direct.[22]

10. POLICY ANALYSIS

The goal of many ABM nonmarket valuation studies is to estimate welfare impacts so they can be used in policy analysis. Welfare measures for the random utility model underlying stated choice methods are relatively well founded and presented in the literature (Small and Rosen 1981; Hanemann 1999; Morey 1999). Since utility is random, the evaluation of welfare measures involves examination of the systematic components of utility as well as the stochastic elements. ABMs provide quantitative measures oftradeoffs between attributes (including price). Thus. they can be used to examine, after an attribute change, how much money would be required to make a person as well off as they were before the change. The fact that ABMs provide estimates of the indirect utility function allows one to calculate these welfare measures for gains, losses, or any combination of change in attributes (assuming that the specification is accurate.)

As defined in equation (I), utility is characterized by systematic (v) and stochastic (E) components. The maximal elements of the utilities over the set of alternatives is defined as $\max(U_j) = \max(v_j + \varepsilon_j)\ \forall j$. Following Morey (I 999), we can express the expected value of the maximum as:

$$(12)\qquad E(U) = \int_{\varepsilon_1=-\infty}^{\infty} \ldots \int_{\varepsilon_J=-\infty}^{\infty} \max(v_1 + \varepsilon_1, \ldots, v_J + \varepsilon_J) f(\varepsilon_1, \ldots, \varepsilon_J) d\varepsilon_1 \ldots d\varepsilon_J$$

where equation (12) integrates utilities over all stochastic terms (densities defined by f(.) associated with each alternative).[23] If a type I extreme value distribution is assumed for the stochastic elements. the expected value of the maximum can be specified as

$$(13)\qquad E(U) = \ln\left(\sum_{j=1}^{J} \exp(V_j)\right) + D$$

where expression (13) is the "log sum" plus a term known as Euler's constant (D).[24] This expression forms the basis for welfare measurement in the multi-alternative case.

In a simple situation where the marginal utility of money is constant (and expressed as λ_Y), an expression for compensating variation can be formulated as follows. Compensating variation (CV) is the amount of money that must be given to or taken away from a person to make him or her as well off after a change as they were before a change. Thus, let "before the change" be expressed as the expected value of the maximum utility in the base case: $E(U)^0 = E(U(Y^0, P^0, X^0))$, where Y is income, P is price, X is the set of attributes. and E is the expectation operator. Let "after the change" be represented by $E(U)^1 = E(U(Y^0, P^1, X'))$, where for generality either price, or attributes, or both can change. Compensating variation is calculated by solving the expression $E(U(Y^0, P^0, X^0)) = E(U(Y^0 - CV, P', X'))$ for the value CV. Using the expression for the expected value of the maximum, and assuming zero income effects, CV becomes

$$(14)\qquad CV = (1/\lambda_Y)\left[\ln\left(\sum_{j=1}^{J} \exp(V_j^1)\right) - \ln\left(\sum_{j=1}^{J} \exp(V_j^0)\right)\right]$$

which is simply the difference in the two expected values of maximum utility (change in utility), divided by the marginal utility of money.[25] The marginal utility of money parameter, in this simple case, is just the parameter on the price variable, with the sign change to reflect increasing utility with income increases. Note that the welfare measure described in equation (14) is for single choice occasions (e.g., one camping trip) or is per choice occasion."' That is. the random utility model is implicitly specified for a given time period (such as a week or day) and the welfare measure applies to this time period. A model of camping destination choice. for example. may be applied to the choice of site each week, where in many weeks the choice will be to "stay at home" or not go camping..

Jhc expression in equation (14) is relevant to cases with multiple alternatives as in the case of recreation sites. alternative products. and so forth. However, choice experiments are also used to compare "states of the world", or a base case described by a single alternative against an altered case described by a single alternative. For example. two new states of the world described by attributes could be presented along with the current situation. These new states of the world could involve improved attribute levels and a positive payment amount. reduced attribute levels and a negative payment amount (refund). or some combination of these conditions. Expression (13) then reduces to

$$(15) \qquad CV = (1/\lambda_Y)[V^1 - V^0]$$

where V^1 and V^0 are the expressions of utility for the base and altered cases. Finally, if V^1 and V^0 are linear in attributes, and the goal is to evaluate a change in a single attribute, equation (15) reduces to the ratio of the attribute coefficient and the marginal utility of money.[27] The resulting values are known as "implicit prices" or marginal willingness to pay.

Note that in most simple ABMs, income **is** not included in the utility function (since income drops out of the utility difference expression). This means that income effects, to the extent that they exist. are ignored. In this case. the utility function specified can be used to measure compensating or equivalent variation, and the! will be identical. More complex forms of random utility models do include income effects.

Readers will notice that we have not discussed willingness to accept (WTA) nor have we discussed the difference between willingness to pa! (WTP) and WTA as this relates to ABMs. That is because ABMs result in specification of indirect utility functions and the specification of the indirect utility function will dictate the difference between WTA and WTP, if any. If a simple linear utility function is specified. income effects are assumed to be zero. Furthermore, these simple utility functions seldom contain any reference point measures or endowment effects. Therefore, in this case it is assumed that there is no difference between WTP and WTA. Some researchers have examined indirect utility functions with income effects and with reference points (e.g. Adamowicz et al. 1998) and we expect this to become more common practice in the future.

11. APPLICATION

The foregoing concepts lay out the basic methods used in designing. analyzing. and interpreting **an** attribute-based experiment. To clarify the concepts and fill in some of the details that we have omitted so far, we present an empirical example based on data collected in a mail survey regarding Maine residents' preferences for alternative timber harvesting practices. For purposes of this chapter. the following example is modified from data descriptions and analyses presented elsewhere (Boyle et al. 2001; Holmes **and** Boyle 2002).[28]

Timber harvesting practices in Maine have received a great deal of public attention. In 1989, the Maine legislature passed a Forest Practices Act that provides rules regarding timber harvesting standards. However, public concern about some provisions of the Act, particularly regarding clearcutting (removing all trees from a harvest area), led to a number of initiatives to modify the Act. Although none of the initiatives have 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.

After discussions with forestry experts. stakeholders, and focus groups. a policy proposal and a set of timber harvesting attributes were selected for the experiment. The policy proposal was for the state of Maine to purchase a large tract of forest land from the timber industry and **to** manage a set of forestry attributes on the tract. Table 5 presents a set of forestry attributes and the attribute levels used for our example. In addition. thirteen different tax prices. ranging from $1 to $1,600 for a one-time tax payment, were included in the experimental design. Alternatives were created by randomly selecting attribute levels for each individual in the sample. The data here consist of N = 156 observations in which the choice set included 4 alternative management plans plus the option to select the status quo (no public purchase of private forest land). An example choice question is shown in Table 6.

Table 5 Forestry attributes and levels for Maine timber harvesting example

Attribute	Level
Live trees left after harvest	No trees (clearcut)
	153 trees/acre (heavy selection harvest)
	459 trees/acre (light selection harvest)
Dead trees left after harvest	Remove all
	5 trees/acre
	10 trees/acre
Percent of forest set aside from harvesting	20% set aside from harvesting
	50% set aside from harvesting
	80% set aside from harvesting

For each L-level, non-price attribute, L 1 variables were constructed to specify the qualitative timber harvesting attributes. Table 7 presents the effects codes associated with each attribute level. Using effects codes, a base level is chosen. If dummy variables were used, this would be the level assigned zeros throughout the data set. With 3 levels only 2 unique parameters can be estimated. When using effects codes, the two unique parameters are summed minus one (the omitted level would be coded as 0 if we used dummy codes)

Table 6 A timber harvesting plan choice set

Attribute	Alternative				
	Plan A	Plan B	Plan C	Plan D	I would not vote for any of the plans
Live trees	No trees	*459*	No trees	153	
Dead trees	Remove all	Remove all	5	10	
Percent set aside	*80%*	*20%*	*50%*	*20%*	
Tax	$40	*$200*	*$10*	$80	
I would vote for: (please choose one box)	☐	☐	☐	☐	☐

and multiplied by 1 to create the parameter value for the base level. When using dummy variables, the parameter value for the base level is assumed to be zero. Note how the base (omitted) levels for the attributes are coded using -1 in the effects codes. In addition. an ASC was included in the specification to estimate the change in utility associated with choosing the status quo alternative.

The results from maximum likelihood estimation of a MNL model are shown in Table 8. All of the preference weight parameters of the indirect utility function have t-statistics greater than 1.64 (90 percent confidence level) except "selection harvest-light" and "5 dead trees/acre". Preference weights for the base (omitted) attribute levels were computed as the sum of 1 times the preference weights on the included levels for each attribute. Marginal WTP values (the WTP for a marginal change in the attribute) were then computed by dividing the preference weights by the marginal utility of money (- 1 times the preference weight for the tax attribute). As can be seen, clear-cutting, leaving no dead trees after harvest and setting aside 80 percent of the forest from

Table 7 **Effects codes for** the timber harvesting attributes

Attribute	Effects code 1	Effects code 2
Live trees left after harvest		
Clear cut	1	0
Selection harvest - heavy (base level)	1	1
Selection harvest - light	0	1
Dead trees left after harvest		
Remove all (base level)	1	-1
5 dead trees/acre	1	0
10 dead trees/acre	0	1
Percent forest set aside from harvest		
20% set aside (base level)	1	-1
50% set aside	1	0
80% set aside	0	1

harvest have relatively large negative impacts on indirect utility. Conversely, a heavy selection harvest, leaving 10 dead trees per acre and setting aside 50 percent of the forest from harvest have relatively large positive impacts on indirect utility.

An interesting interpretation can be made for the preference weight on the ASC. Recall that, as defined here. the ASC represents the utility of choosing the status quo alternative, everything else held constant. The negative sign indicates that choosing the status quo decreases indirect utility (choosing alternatives to the status quo increase indirect utility). This result is consistent with the degree of political activity in Maine seeking alternatives to current timber harvesting practices. The respondents would prefer to see a change from the status quo even if all attributes were held constant. This indicates a significant desire to have some change in the policy environment. If a positive sign on the ASC were found. it would indicate a positive preference for the status quo (everything else held constant) and would be consistent with the more common status quo "bias" found in the literature. in which individuals attach some positive utility to the status quo situation.

The pseudo R^2 for the overall model. computed as I minus the ratio of log-likelihood at convergence and log-likelihood at zero, is 0.14. The ASC accounts for 0.03 of the pseudo R^2 value. The attributes included in the example clearly had a dominant role in explaining choice among the timber harvesting alternatives.

12. RELAXING THE ASSUMPTIONS OF THE CONDITIONAL LOGIT MODEL

Up to this point. two assumptions have been made to simplify the econometric analysis of the conditional logit model. First. we assumed that everyone in the population has the same preference structure. T-his assumption restricts the β's to be the same for all members of the population. Second, we assumed that the ratio of probabilities between any two alternatives was unaffected by other alternatives in the choice set. This property (IIA, section 7) results in limited substitution possibilities.

Table 8. Parameter estimates for the timber harvesting choice experiment example

Attribute	Preference weight	t-statistic	Marginal WTP
ASC (for status quo alternative)	-1.15	-1.36	—
Clearcut	-0.42	-2.79	-22105
Selection harvest - light	0.08	0.57	32.11
Selection harvest - heavy (base level)	0.34		178.95
5 dead trees/acre	0.09	0.66	47.37
10 dead trees/acre	0.32	2.42	173.68
No dead trees (base level)	-0.41	—	-215.79
Set aside 80 percent	-0.29	-1.88	-152.63
Set aside 50 percent	0.34	2.50	178.95
Set aside 20 percent (base level)	-0.05	—	-26.32
Tax	-0.0019	-4.361	
Log-likelihood at zero	-251.07		
Log-likelihood at constants	-243.46		
Log-likelihood at convergence	-215.39		
Likelihood ratio (pseudo-R^2)	0.14		

12.1 Relaxing the Assumption of Common Preferences: Heterogeneity

The basic conditional logit model described in equation (6) implicitly assumes that preferences are identical, for all respondents (the parameters in the conditional indirect utility function are constant). This simplifying assumption can be altered by three modifications: (1) including interaction effects, (2) estimating a latent class/finite mixture model. and (3) using a random parameter/mixed logit approach.

12.1.1 Interaction Effects

Individual (respondent) specific variables (age. wealth. etc.) cannot be examined directly in a conditional logit model because these variables do not vary across alternatives. Thus, individual specific variables drop out of the utility difference. However, individual specific variables can interact with alternative-specific attributes to provide some identification of attribute parameter differences in response to changes in individual factors. For example. interacting age with the price attribute would generate information on the marginal utility of money (price) as a function of age. This is a simple approach that provides insight into heterogeneity of consumers. but it assumes the researcher already knows the elements that lead to heterogeneity (those items included as interaction effects) and results in many parameters and potential collinearity problems.

12.1.2 Latent Class/Finite Mixture Approach

A better, although somewhat more complicated, approach is to use a latent class/finite mixture model. Suppose S segments exist in the population, each with different preference structures, and that individual n belongs to segment s (s = 1,...,S). The conditional indirect utility f-unction presented above can now be expressed as $U_{in|s} = \beta_s X_{in} + \varepsilon_{in|s}$ The preference parameters (β) vary by segment. The probability ofchoosing alternative i depends on the segment that one belongs to and can be expressed as:

$$P_{n|s}(i) = \frac{\exp(\beta_s X_i)}{\sum_{k \in C} \exp(\beta_s X_k)} \tag{16}$$

where β_s are segment-specific utility parameters (and scale is fixed at I).

Now let there be a process describing the probability of being in a particular segment, as a function of demographic (and other) information. Following Boxall and Adamowicz (1999), Swait (1994), and Gupta and Chintagunta (1993). that process can be specified as a separate logit model to identify segment membership as:

$$P_{ns} = \frac{\exp(\lambda_s Z_n)}{\sum_{s=1}^{S} \exp(\lambda_s Z_n)} \tag{17}$$

where Z is a set of individual characteristics and λ is a vector of parameters.

Let P,,(i) be the joint probability that individual n belongs to segment s and chooses alternative i. This is also the product of the probabilities defined in equations (16) and (17): P,,(i) $= P_{ns}$ P,,,(i). The probability that individual n chooses i becomes the key component in the finite mixture or latent class approach:

$$P_n(i) = \sum_{s=1}^{S} \pi_{ns} \; \pi_{n|s}(i) \,. \tag{18}$$

Note that this approach provides information on factors that affect or result in preference differences. That is. the parameters in the segment membership function indicate how the probability of being in a specific segment is affected by age, wealth. or other elements included in the segment membership function. Further detail on this approach to heterogeneity can be found in Swait (1994), Boxall and Adamowicz (1999) or Shonkwiler and Shaw (1997).

12.1.3 Random Parameter/Mixed Logit Approach

Another approach to identifying preference heterogeneity is based on the assumption that parameters are randomly distributed in the population. Then, the heterogeneity in the sample can be captured by estimating the mean and variance of the random parameter distribution. 'This approach is referred to as random parameter logit (RPL) or mixed logit (Train 1999) modeling.

Let the conditional indirect utility function be as specified in equation (I). Assume that the parameters (β) are not fixed coefficients but rather are random coefficients that follow a predetermined distributional for-m. The probability expression from the conditional logit model

$$P(j) = \frac{\exp(X_j\beta)}{\sum_{k \varepsilon C} \exp(X_k\beta)} \tag{19}$$

is modified to reflect the fact that β has a distribution. Following Train (1999) the overall probability is expressed as the conditional probability (conditional on β) integrated over values of β, or:

$$(20) \qquad P(j) = \int \pi_j(\beta)\; g(\beta)\; d(\beta)$$

Given a choice of a specific distribution for β (or assumptions on $g(\beta)$) such as normal or log-normal, estimation of the choice probabilities proceeds with providing estimates of the mean and variance of those parameters assumed to be random. Note that if $g(\beta)$ is constant or degenerate, this model reduces to the standard conditional logit model. Also, note the similarity of equation (20) to equation (18). Both are essentially weighted conditional logit models. Equation (18) reflects a finite weighting or mixture, whereas equation (20) is a continuous mixture. See Train (1999), Revelt and Train (1998), or Layton (2000) for details.

12.2 Relaxing the IIA Assumption

The simple conditional logit model produces probabilities of the form expressed in equation (19). However, the ratio of probabilities for any two alternatives (i and j) results in:

$$(21) \qquad \frac{P(i)}{P(j)} = \frac{\exp(V_i)}{\exp(V_j)}$$

Thus the ratio of probabilities between i and j is unaffected by **any** other alternative in the choice set, and the conditional logit model depends on the IIA property. This property results in elasticities that are limited in flexibility and generally produces substitution patterns that are simplistic (the elasticities of the probability of choosing alternative j with respect to a change in an attribute in alternatives other than j are all equal). **In** the simple camping choice experiment, for example, the two camping alternatives would likely be more similar or there would be unobserved correlation between these alternatives, relative to the opt-out alternative. However, in the conditional logit formulation, there is no correlation between the unobserved effects (errors) of the alternatives. A further implication of choosing the conditional logit model is that the cross elasticities (the percent change in probability of choosing i for a percent change in an attribute level in any alternative j) are identical. This is a highly restrictive form of preference.

12.2.1 Nested Logit

An approach to address these issues is to estimate a nested logit model (McFadden 1981; Ben-Akiva and Lerman 1985; Louviere, liensher, and Swait 2000). Suppose we consider the camping example above, but assume that camping alternatives (A or B) are similar relative to the alternative of not going camping (C). The choice of alternatives A, B. or C could be specified as the probability of choosing an alternative, conditional on the probability of going camping (A or B) versus (C). Utility would be decomposed into utility associated with camping versus not camping. and utility arising from camping sites (A or B) conditional on going camping. In terms of probability expressions, this is reflected as follows. Let j index alternative sites and m index activities (going camping or not). The utility ofchoosing sitej in activity m (camping) can be expressed as:

(22) $$U_{jm} = U_{j|m} + U_m = V_{j|m} + V_m + e_{j|m} + e_m$$

The two error terms ($e_{j|m}$ and e_m) reflect the unobserved variation in alternatives j (conditional on m) and m. Assuming independence between the two error terms. one can show that the joint probability of choosing alternative jm is

(23) $$P(jm) = \frac{\exp a_m(V_m + V_{m^*})}{\sum_{m'=1}^{M} [\exp a_m(V_{m'} + V_{m'^*})]} \cdot \frac{\exp(V_{j|m})}{\sum_{j'=1}^{J} [\exp(V_{j'|m})]}$$

where V_{m^*} is $(1/a_m) \log \sum \exp (V_{j|m})$ or the "inclusive value" or "log-sum" and a_m is the parameter on the inclusive value. The inclusive value term captures the utilities (the expected value of the maximum utility) of the camping alternatives within the utility associated with the activity camping. If $a_m = 1$, then the expression collapses to the simple logit expression. An inclusive value parameter of I corresponds to equal correlation between the alternatives and an inclusive value parameter between zero and I indicates the degree of correlation (or similarity) between alternatives within a particular activity.

Expression (22) can also be considered to bc the product of probabilities. The probability ofchoosing alternative j and activity m can be expressed as the product of the probability of choosing alternative j. conditional on choosing activity m, times the probability of choosing activity m. In other words, the probability of choosing camping alternative j is the product of the probability of choosing camping (versus not camping) times the probability of choosing alternative j conditional on choosing camping, or:

$$P(j,m) = P(j\,|\,nr)\ \ P(m) \tag{24}$$

The nested logit model (nesting the decision of where to go camping within the decision to go camping or not) does not have the IIA proper? and relaxes the assumption of identical substitution elasticities. However, a more interesting interpretation of the nested logit model, in terms of error variance components. is provided below through the description of the mixed multinomial logit model.

12.2.2 Mixed Multinomial Logit Models: Error Components

Random parameter models were described in Section 12.1.3 as one outcome of a mixed logit structure. An alternative interpretation of mixed logit can he used to construct nested logit models. as well as a variety of other models that involve correlation between the unobserved elements of the alternatives. Following Train (1998, 1999), let the conditional indirect utility of alternative j be expressed as

$$V_j = \beta X_j + \mu Z_j + \varepsilon_j \tag{25}$$

where ε_j is an IID *extreme* value error term (extreme value is chosen to be consistent with the logit framework), and μZ_j represents an additional stochastic component of the utility. Let μ be a mean zero term. The inclusion of μZ_j in the stochastic component of the utility function allows alternative-specific elements to enter the stochastic portion of utility, and thus allows for the examination of various correlations of unobserved effects. As Train (1999) illustrates. defining Z_i as a dummy variable for a subset of the overall set of alternatives (e.g., camping alternatives) provides an estimate of the error correlation among this subset ofalternatives. and the variance on μ becomes an estimate of the correlation or the inclusive value parameter. Note that if μ is zero and non-random, the conditional logit model results.

Estimation of such a model relies on the relationship between the mixed logit/random parameters model specified above and the error components model. If $X_i = Z_i$, the parameter β can be interpreted as the mean while μ can be interpreted as the variance. In an error components interpretation, one is most interested in the correlations between alternatives (as in nested logit models) as captured by the stochastic terms (Brownstone and Train 1996; Revelt and Train 1996). Nevertheless, the estimation of these models follows the approach presented in equations (i 9) and (20) above.

13. FUTURE DIRECTIONS

These are still early days in the application of ABMs to environmental valuation. Researchers continue to evaluate the effectiveness of these methods. Efforts to improve design and analysis of data generated by ABMs are on-going. The current literature can be divided into these components: evaluating and testing ABM performance, improving econometric analysis of ABM data, and improving ABM designs.

13.1 Evaluation and Testing of ABM Performance

Many writers have speculated that ABMs may outperform contingent valuation with respect to strategic behavior. hypothetical bias. or a variety of other challenging issues associated with stated preference methods. However, very few tests of ABM performance have been conducted. Recent results from Carlsson and Martinsson (2001) suggest that ABMs perfonn very well relative to market or experimental market choices. In addition, studies like that of Haener, Boxall, and Adamowicz (2000) show that ABMs do a good job in predicting "out of sample" (data not included in the sample used for estimation) choices. Nevertheless, additional research is required to evaluate ABM Performance and subject ABMs to the same level of scrutiny as contingent valuation methods have received in the past.

13.2 Econometric Analysis

Attribute-based methods are often administered such that individuals respond to several ranking, rating, or choice tashs. Presenting respondents with as many as 16 such tasks is not unusual. In simple econometric analysis, these tasks are assumed to be independent. However, some empirical and much anecdotal evidence suggests that these responses are not independent. Respondents may learn about their preferences, or they may become fatigued during the survey. In general, the responses may be serially correlated, or at least should be treated as arising from panel data. Mixed multinomial logit models offer econometric methods to address correlations between choice sets and panel data considerations within discrete choice/random utility data (e.g., Train 1999; Revelt and Train 1998, McFadden and Train 2000). However, in addition to simple correlation between alternatives, issues of fatigue and learning may be better represented as systematic preference changes in response to sequences ofquestions. Swait and Adamowicz (2001a) provide one approach to such an issue by examining preference variation with a finite mixture model operating on question order and task complexity. Certainly, other approaches also could be explored to assess the implications of question order. serial correlation. and stated preference question response.

In addition to serial correlation, research on cotnbining data types. or data fusion, is on-going. If revealed preference responses suffer from collinearity, or from limited data range, ABMs can facilitate the estimation of parameters that are difficult or impossible to measure using revealed preference data alone. Evidence suggests that joint revealed and stated preference models outperform revealed preference methods within samples (Adamowicz, Louviere. and Williams 1994) as well as in out-of-sample prediction tests (Haener, Adamowicz and Boxall 2000). However, many unanswered questions in data fusion remain including the following three: What weight should be placed on each data type'? Are there more efficient ways to combine data? Can combining ABM data with small samples of revealed preference data provide better benefits transfers than transfers of revealed preference data from other regions?

13.3 Design Issues

Psychologists and researchers in human judgment and decision making have long focused on the effect of changes in decision context on response and implied behavior. Similar issues arise in ABM surveys. Dochanges in context affect responses? Are these effects systematic and could they be examined econometrically? Currently rules-of-thumb are used to determine the number of attributes, alternatives, and questions, and orthogonal designs are heavily relied upon to generate the correlation structure between alternatives. However, these rules-of-thumb have not been rigorously examined. In addition to complexity, other context effects arise. such as the respondent's reference group (family, peer group, etc.) and the degree to which these elements affect preferences. Although economists have historically focused on individual responses. there is increasing interest in examining demand and preference as arising from groups such as households (Smith and van Houtven 1998 among others) or as being affected by reference groups (Manski 2000 or Brock and Durlauf 1995 among others).

14. CONCLUSIONS

ABMs have emerged from a creative linkage of research across disciplines including marketing, psychology, transportation and economics. Through this process. the hedonic framework articulated by Lancaster more than 3 decades ago has been refined by developments in random utility theory, econometrics and experimental design into a set of powerful tools that provide economists with new methods for environmental valuation. If carefully designed and administered, ABMs can provide defensible estimates of environmental value for behavioral analysis (such as recreational choice) or passive use valuation. However, without careful attention to framing the decision contest, applying an appropriate experimental design, developing a focused survey instrument and implementing robust empirical procedures, ABM applications will not provide the desired information.

These are still early and exciting days in the application of ABMs to environmental valuation. As stated preference methods. ABMs are closely related to contingent valuation methods and face similar issues relating to the validity of responses. Assessment of the validity and consistency of ABM responses will undoubtedly be an important avenue of future research. However, research to date combining stated and revealed preference data indicates that ABMs, when properly applied, can provide information on preferences that is consistent with actual behavior. We anticipate that future research on ABMs will not only provide a deeper understanding of environmental preferences but will also enhance other applications of stated preference methods.

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NOTES

The term "conjoint" arose from early attempts to examine a set of attributes at the same lime or "consider jointly" Traditional conjoint analysis involved ratings Some authors refer to the methods we describe in this chapter as being examples of conjoint analysis Others refer to choice methods as "choice-based conjoint" We prefer the term "attribute-based method" because it more explicitly highlights the focus on examination of a bundle of attributes associated with a good and because it leaves open the choice of elicitation approach. whether it be choices between bundles ranking of bundles. or ratings of individual bundles

2 Rating scale approaches, or traditional conjoint analysis, are based on Torgerson's (1958) Law of Comparative Judgment. This approach presents individuals with profiles (alternatives) or bundles of attributes and asks them to provide a rating of each profile (e.g. 1 to 10, where 10 is very good, and 1 is very poor). The development of rating-based conjoint is discussed in Green and Srinivasan (1978) and Louviere (1988b). Axiomatic theories of conjoint analysis have also been developed (Krantz et al 1969, Barron 1977) that deal with the relationship between the ordinal numerical scores provided in conjoint rating tasks and various forms of preferences or utility. One of the earliest empirical studies using rating scales to measure preference parameters concerned preferences for the visual appearance of residential neighborhoods (Peterson 1967).

3 Individual prediction models typically assumed that the best or first choice alternative would be the product that received the highest predicted utility. Summation of first choices across the sample provided estimates of market share. An alternative approach introduced by Louviere and Woodworth (1983) used the predicted utilities in a modified Luce model to predict the probability that an individual would choose competing products. The summation of predicted probabilities over the sample then generated choice frequencies, which were used in a weighted least squares regression of the multinomial logistic model.

4 McFadden (1986) goes on to state that "...it is unnecessary to provide accurate behavioral models individual-by-individual to obtain good market forecasts. It is sufficient to determine the distribution of behavior in the population" (p. 278). The multinomial logit model is based on the assumption that behavior in the population follows an extreme-value type 1 distribution.

5 See also subsequent work by Manski (1977) and Yellot (1977).

6 In addition, Hensher (1994) provides an overview of RUM models in the transportation literature while Louviere (1994) reviews applications in marketing (see also the case study chapters in Louviere, Hensher, and Swait, 2000).

7 See also Swait and Louviere (1993) in the marketing research literature.

8 In Table 2, note that the elements of each column vector sum to zero and that, within sets of main effects and 2-way interactions, the inner product of two column vectors equals zero. This second property defines orthogonality or statistical independence.

9 The alias of any factorial effect can be determined using what the experimental design literature refers to as a defining contrast. In Table 2, note that the 3-way interaction A1A2A3 contains a vector of + l's for the first ½ fraction (and a vector of - l's for the second ½ fraction). A1A2A3 is the "defining contrast" because it was used to split the factorial into two fractions. In a 2^n design, the alias of any factorial effect is found by multiplying the effect by the defining contrast (Cochran and Cox 1957). So, for example, the alias of A3 is the generalized interaction $A1A2A3^2$. Squared terms are canceled in interpreting generalized interactions, so $A1A2A3^2$ is read as A1A2 which, as shown previously is the alias for A3.

10 For a good discussion of various design strategies, see Louviere, Hensher, and Swait (2000).

11 The smallest orthogonal main effects designs for various combinations of attributes, levels and choice options is presented in Louviere, Hensher, and Swait (2000, Table 5.3, p. 121).

12 For example, methods for analyzing panel data when the responses are binary are well known (e.g. Hsiao 1986).

13 Choice experiments often include "opt-out" (none of the offered alternatives) or "status quo" options as fixed alternatives. These are referred to as fixed alternatives because their attribute levels or descriptions do not vary over the set of choices presented to the respondent. Coding of the attribute levels for the status quo option may cause confusion. If attribute levels for the status quo option are known, then they are coded in the usual manner. This would be the case, for example, if the status quo were one of the options in a policy choice set. For another example, consider the options for a recreation choice experiment. If the options included two hypothetical alternatives and an alternative for a currently existing substitute, then the fixed alternative might ask people to provide descriptions of the substitute option (for an evaluation of this approach, see Banzhaf, Johnson, and Matthews 2001). Alternatively, it might be the case that a "generic" opt-out option is included such as "I would choose neither of the hypothetical alternatives" in a recreation choice experiment. In this case, because nothing is known about the attributes of this option, attribute coding is typically handled using zeros for attribute levels of the opt-out option. Because the MNL model is based on utility differences, this approach normalizes utility relative to the opt-out option.

14 For an application of random utility theory to travel cost models, see Chapter 9.

15 Indirect utility in equation (1) modifies the indirect utility function described in Chapter 2 by (1) considering non-market goods to be described by a vector of attributes, and (2) the addition of a random error term. Further, indirect utility described in Chapter 2 is global, in that it encompasses all goods and services in an individual's consumption bundle. The indirect utility function described here is an additively separable sub-utility function that is specific to the particular non-market good under consideration.

16 The multinomial probit model relaxes the assumption of independence of irrelevant alternatives and allows a more general pattern of covariance among alternatives. Empirical difficulties formerly associated with estimating this model have recently been addressed and applications to ABMs are anticipated.

17 The IIA axiom states that the ratio of the probabilities of choosing any two alternatives is independent of the attributes or the availability of other alternatives (e.g. Ben-Akiva and Lerman 1985).

18 Given a single data set, it is assumed that the scale parameter μ equals unity. If $n > 1$ data sets are available, it is possible to estimate the value of μ for $n - 1$ of the data sets (Swait and Louviere 1993).

19 In the MNL model, scale is inversely proportional to the error variance: $\sigma^2 = \pi^2 / 6\mu^2$ where π is the mathematical value 2.1415... and μ is the scale.

20 Ranking data have also been analyzed using an ordered probit specification (e.g., see Boyle et al. 2001).

21 This method is appropriate if a limited number of values are included on the rating scale.

22 There is some literature that suggests that the structure of preferences varies when elicited by different response formats (Huber 1997; Boyle et al. 2001).

23 See Morey (1999) for additional detail on the derivation of compensating variation in logit models.

23 D = 0.57722.

25 See Morey (1999) and Choi and Moon (1997) for details regarding estimation of welfare effects in more complex cases (nested logit models, etc.). Morey (1999) also provides a very good discussion of estimating confidence intervals for welfare measures.

26 Details on integrating welfare measures from choice occasions with changing frequencies of choice occasions (number of trips) can be found in Morey and Waldman (1998), Hausman, Leonard, and McFadden (1995)

27 This still assumes zero income effects.

28 In the original experiment, survey respondents were asked to consider seven timber harvesting attributes Here we reduce the number of attributes to three Also, in the original experiment, rhe "opt-out" option was presented in a sequential manner Here we treat the opt-out option as being presented simultaneously with the other alternatives

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