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Using Choice Experiments to Value the Environment

Design Issues, Current Experience and Future Prospects[1]

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Abstract. This paper we outline the "choice experiment" approach to environmental valuation. This approach has its roots in Lancaster's characteristics theory of value, in random utility theory and in experimental design. We show how marginal values for the attributes of environmental assets, such as forests and rivers, can be estimated from pair-wise choices, as well as the value of the environmental asset as a whole. These choice pairs are designed so as to allow efficient statistical estimation of the underlying utility function, and to minimise required sample size. Choice experiments have important advantages over other environmental valuation methods, such as contingent valuation and travel cost-type models, although many design issues remain unresolved. Applications to environmental issues have so far been relatively limited. We illustrate the use of choice experiments with reference to a recent UK study on public preferences for alternative forest landscapes. This study allows us to perform a convergent validity test on the choice experiment estimates of willingness to pay.

Key words: choice experiments, cost-benefit analysis, environmental valuation, forest landscapes, stated preference models

JEL classification: Q23, Q26

1. Introduction

Environmental valuation has come a long way since the original work on the travel cost model and contingent valuation in the USA in the 1960s. This paper sets out the basic concepts behind a relatively new methodology in environmental valuation, namely "Choice Experiments" (CE) , which tries to address some of the limitations of traditional methods. We provide an account of the theoretical underpinnings of the method, and consider the main design issues involved in a CE study, before reviewing the literature which exists so far in this area. The relationship of CE to other valuation methods is also touched on. We then give a brief account of a CE study of forest landscape change in the UK, as an illustration of how the method can be implemented and the kinds of results which can be achieved. Finally, we consider likely future developments in CE. For a fuller account of the CE method, see Adamowicz et al. (1998b).

The CE technique is an application of the characteristics theory of value (Lancaster 1966), combined with random utility theory (Thurstone 1927; Manski 1977). It thus shares strong links with the random utility approach to recreational demand modelling using revealed preference data (Bockstaell et al. 1991). Respondents are asked to chose between different bundles of (environmental) goods, which are described in terms of their attributes, or characteristics, and the levels that these take. One of these attributes is usually price. For example, consider a respondent's choice of fishing location. Assume that utility depends on choices made from some set **C** of alternative sites. The representative individual is assumed to have a utility function of the form:

$$U_{in} = U(Z_{in}, S_n) \tag{1}$$

where, for any individual n, a given level of utility will be associated with any alternative fishing site i. Alternative i will be chosen over some other option j iff $U_i > U_j$. Utility derived from any option is assumed to depend on the attributes, Z, of that option (for example, water quality and the nature of the surrounding landscape). These attributes may be viewed differently by different agents, whose socioeconomic characteristics S will also affect utility. Assume now that the utility function can be partitioned into two parts; one deterministic and in principle observable, and one random and unobservable. Then Equation (1) can be re-written as:

$$U_{in} = V(Z_{in}, S_n) + \varepsilon(Z_{in}, S_n) \tag{2}$$

and the probability that individual n will choose option i over other options j is given by:

$$\text{Prob}(i \mid \mathbf{C}) = \text{Prob}\{V_{in} + \varepsilon_{in} > V_{jn} + \varepsilon_{jn}, \text{all } j \in C\} \tag{3}$$

where **C** is the complete choice set. In order to estimate Equation (3), assumptions must be made over the distributions of the error terms. The usual assumption made is that the errors are Gumbel-distributed and independently and identically distributed (McFadden 1974). This implies that the probability of choosing i is given by:

$$\text{Prob}(i) = \frac{\exp^{\mu v_i}}{\sum_{j \in C} \exp^{\mu v_j}} \tag{4}$$

Here, μ is a scale parameter, which is usually assumed to be equal to 1 (implying constant error variance). As $\mu \to \infty$, the model becomes deterministic. Equation (4) is estimated by means of a multi-nomial logit regression, which assumes that choices are consistent with the Independence from Irrelevant Alternatives (IIA) property. This states that "...for any individual, the ratio of choice probabilities of any two alternatives is entirely unaffected by the systematic utilities of any other alternatives" (Ben-Akiva and Lerman 1985: 108). CE data sets can be tested for this IIA property, but if IIA is found to be violated, then the standard random utility model can no longer be applied.[2]

If $V(\cdot)$ is linear such that $V = \beta(\mathbf{X}_n)$, where $\mathbf{X}$ is a vector of observable attributes, and β a vector of parameters to be estimated, then, assuming two choice alternatives, i and j, the model becomes:

$$\text{Prob}(i) = \frac{e^{-\mu\beta'(X_{in}-X_{jn})}}{1 + e^{-\mu\beta'(X_{in}-X_{jn})}} \tag{5}$$

The CE approach is essentially a structured method of data generation. It relies on carefully designed choice tasks that help reveal the factors influencing choice. Designing a CE requires careful definition of the attribute space (including attribute levels and ranges) such that the attribute space includes the portion relevant for the policy questions being asked. Furthermore, the CE approach involves the use of statistical design theory to construct choice scenarios which can yield parameter estimates that are not confounded by other factors. These orthogonal designs are important from the point of view of isolating the effects of individual attributes on choice, and the ability to "design in" this orthogonality is an important advantage over revealed preference random utility models, where attributes in reality are often found to be highly correlated with each other.

Since CE models share the same random utility framework as Dichotomous Choice (DC) CVM models (Hanemann 1984), the welfare estimates from each are directly comparable. This is perhaps most obvious from the utility difference format of Equation (5). CE results, for the same reason, are also directly comparable with random utility travel cost models. As Adamowicz et al. (1994) show, consumers' surplus estimates for changes in attribute levels can be derived from the logit equation implicit in Equations (4) and (5). This is based on an interpretation of the coefficient on the "price" attribute in the logit equation as equal to the marginal utility of income. In addition, the consumers' surplus of increasing all attribute levels simultaneously can be calculated. For the case of two alternatives and a linear indirect utility function, this involves merely summing the marginal values for each attribute in moving from a lower level of the attribute $(z_1{}^1)$ to some higher level $(z_1{}^2)$. For a quadratic indirect utility function this implies solving for the compensating surplus, CS, in the following equation:

$$V_1 = a_1(Y) - a_2(Y^2) + b(Q_1) = a_1(Y - CS) - a_2(Y - CS)^2 + b(Q_2) = V_2 \tag{6}$$

where V_1 is the initial level of utility, V_2 is subsequent level of utility, Q_1 is the lower level of environmental quality, Q_2 is the higher level of environmental quality, Y is income, and a_1, a_2, and b are parameters to be estimated.

Relative to CVM, the CE method would seem to possess several advantages. These are:

- It is easier to estimate the value of the individual attributes that make up an environmental good, such as landscape. This is important since many management decisions are concerned with changing attribute levels, rather than losing or gaining the environmental good as a whole (the issue which CVM is more able to address).
- CE provides the opportunity to identify marginal values of attributes that may be difficult to identify using revealed preference data because of co-linearity or lack of variation.
- Because of this, CE may offer advantages over CVM in terms of benefits transfer, if environmental goods can indeed be decomposed into measurable attributes with money values which can be estimated; and if socioeconomic variable are included in the CE models used.
- CE also avoids the "yea-saying" problem of DC design CVM (Ready, Buzby and Hu 1996; Brown et al. 1996), since respondents are not faced with the stark "all or nothing" choice in that design of CV. They may choose one of two environmental alternatives, or the status quo, in each choice pair, of which they receive many. There are thus repeated opportunities for them to express their environmental preferences within a CE design.
- Adamowicz (1995) and Adamowicz et al. (1998b) have speculated that CE may be a good way around the embedding problem encountered in CVM since tests of scope are essentially built in to the CE.
- The repeated sampling approach of CE allows for internal consistency tests in the sense that models can be fitted on sub-sets of the data.

2. General Issues in Choice Experiment Design

In any CE study, a number of important decisions are made at the design stage. These include the number of attributes, the number of levels to allow each attribute to take, what these levels should be, and how both levels and attributes should be described. A bid vehicle (that is, a way of expressing the price of the environmental good) must be established, just as in CVM, and the levels this takes. In addition, a decision must be made over whether to allow each attribute to enter choices on its own, or also in combination with other attributes. For example, suppose we specify four attributes for woodland landscapes, in conjunction with focus groups and landscape designers, and that a bid vehicle of local taxes has been decided on. Suppose the woodland attributes are species mix (S), age diversity (A), the percentage of forest as open space (C), the existence of forest roads (R) and the price to the individual of the forest design (P). Then a simple choice model would evaluate design i in terms of:

$$Z_i = f(S_i, A_i, C_i, R_i, P_i) \quad (7)$$

This is known as a main effects design. If S, A and P take four possible levels, and C and R take two possible levels (for C this might be more or less than 30% of the land area as forest), then the total number of combinations are ($4^3 \times 2^2$). However, we might speculate that these variables should also be included as quadratic and even cubic terms, as a simple linear relationship is not sufficient. Finally, we might assume in addition that cross-effects need to be included; for example, an interaction term between species mix and age diversity, and between open space and forest roads. Such changes obviously increase the size of the experimental design.

Typically, in a CE, respondents will be offered multiple choices: two alternative designs of the environmental good (say *A* and *B*), and the option to choose neither. Each such triple is known as a choice occasion. This, in the main effects model above, implies a possible combination of $\{(4^3 \times 2^2) \times (4^3 \times 2^2)\}$. Using design software, a sub-set of this universe of possible choices exists which will enable the parameters of the model to be estimated. If this sub-set is thought to contain too many choices for an individual to be reasonably expected to make (and there seems to be great debate how many is "too many" in this case) then the design can be "blocked" by specifying an additional variable which takes *n* levels, where *n* is defined by the ratio of the size of the subset to the maximum number of choices to be presented to each individual (for a discussion of experimental design, see Louviere 1988a).

There is also a concern over whether the essential nature of an environmental asset, such as a wetland, can be described in terms of its individual components. There are two problems here. First, the value of the wetland in its totality may be greater than the sum of attribute values (the value of the whole being greater than the sum of the parts). For example, hydrological and ecological integrity might be important. Second, the manner in which experimental design treats attributes, in terms of the orthogonal, main effects design used in CE, may be at odds with ecological realities. For example, some minimum quantity of attribute *A* might need to be present before attribute *B* becomes viable. These two problems may be thought of as relating thus to both how people perceive the environment, and how the environment itself works.

A final issue concerns the modelling of participation decisions, where use values (recreational values) concerned, for example, in terms of the effects on welfare of characteristic changes at fishing sites. By including an Alternative Specific Constant (ASC) for each site (*A* or *B*), non participation can be allowed for. ASCs also allow for non-observable attributes to influence site choice. An alternative would be to build a nested model which takes as a first step the decision whether to fish or not, and then models the decision over which site to visit. In Adamowicz (1997), for example, such a nested model proved inferior to a conditional single-step logit model with ASCs.

3. Recent Use of Choice Experiments

The term "Choice Experiments" seems to have been first used by Louviere and Woodworth (1983). The CE technique was first applied to environmental management problems by Adamowicz et al. (1994), although many applications in other fields (notably marketing and transport economics) predate this (see Louviere and Woodworth 1983; Louviere 1988; Louviere 1992). It is also worthwhile pointing out that the term "conjoint analysis" is somewhat broader in coverage than CE, since the former includes ranking exercises, of which Contingent Ranking is the obvious equivalent in the environmental valuation literature (Foster and Mourato 1997). Conjoint analysis also includes methods from marketing which look similar statistically to CE or contingent ranking, but which lack the random utility basis of CE and contingent ranking.[3]

The CE technique differs from contingent ranking in terms of the nature of the choice task; in the former approach, respondents make pairwise choices: in the latter, they are asked to rank a series of alternatives (for example, four different forest designs). The approaches also differ somewhat in terms of the statistical models employed (see Beggs et al. 1981).

Adamowicz et al. (1994) apply CE to the evaluation of recreationalists' preferences for alternative flow scenarios for the Highwood and Little Bow rivers in Alberta, Canada. The survey enabled a revealed preference study to be undertaken too, and for both data sets to be combined into one model. Choice sets were constructed for two river types (standing water and running water); eight attributes were specified as common to both types, including terrain, fish size and water quality. In addition three more attributes were specified for standing water and two for running water. All attributes were given either four or two levels. Price was proxied by travelling distance to the site. Respondents viewed sixteen choice sets, and in each case were asked to choose either a running or standing water site, or no site (that is, to make no trip). Results showed that attributes such as water quality and fish catch were significant determinants of trip destination: consumer surplus per trip (use value) varied from CDN \$8.06 to \$4.33. The authors also report a revealed preference model of the same sites/attributes, and a pooled model.

Boxall et al. (1996) report the results of a CE applied to recreational moose hunting in the province of Alberta. This study also collected CVM responses, to allow welfare estimates from the two techniques to be compared. The attributes included in the CE design were distance from home to hunting area, quality of road access, access within hunting area, encounters with other hunters, forestry management operations in the area, and moose population (evidence of more or less than one moose per day). This gave a $\{(4^4 \times 2^2) \times (4^4 \times 2^2)\}$ design size, given that respondents were offered three choices: visit site A, visit site B, or do not go hunting. The CVM question involved willingness to incur additional travel costs to access an area with a higher moose population than a closer area, structured as a yes/no response to a given additional cost. Results in the CE showed that all attributes except road quality and forestry management operations were significant and of the expected sign (for example, seeing no other hunters increased utility). The CVM model only allowed the welfare gain from increasing one attribute (moose population) to be estimated, whilst the CE model allowed gains for increasing all (desirable) attributes to be calculated. The Willingness to Pay (WTP) per trip for an increased moose population was much lower for the CE data than for the CVM data. Tests showed that this may have been due to respondents in the CVM sample ignoring substitution possibilities (that is, the option to visit a different site to the two contained in the WTP question). The authors suggest that the ability of CE to better capture substitution possibilities, and to incorporate a wider range of environmental quality changes, may be important advantages over CVM.

Adamowicz et al. (1998b) present the first application of CE to estimating non-use (passive use) values. Again, both CE and CVM responses were collected. The study focused on the protection of old-growth forests in west central Alberta, from the perspective of safeguarding caribou populations (a threatened species in Alberta). The CVM question involved the restriction of recreational and commercial forestry activities to allow caribou to increase to a "minimum viable population", using higher taxes as the payment vehicle. The CE questionnaire contained alternative woodland designs described in terms of five attributes (caribou population, area of wilderness, recreational restrictions, forest industry employment and provincial income tax level). Each attribute took one of four levels: the status quo, one level below this, and two above it. Since attributes varied both above and below the status quo, both WTP and WTAC (willingness to accept compensation) could be estimated. Each respondent received eight choice sets, and respondents were chosen as a random sample of residents in Edmonton.

Results in the CE showed that all attributes except employment were significant with the expected signs. The linear model was outperformed by the quadratic model, since the quadratic terms all had high t-statistics. A test showed that the attribute parameters did not differ significantly between the CE and CVM models, when the scaling effect was allowed to be heterogeneous: this might be considered to be a test of convergent validity. Error variances were not significantly different between the two models. A quadratic model gave higher welfare measures than a linear model for improvements in caribou populations. Finally, the authors were able to demonstrate the existence of an endowment effect under WTAC scenarios (in other words, a negative utility being associated with moving away from the status quo). This follows from the result that the alternative specific constant was negative and significant.

Adamowicz et al. (1997) introduce the innovation of comparing respondents' own subjective rating of attributes, with objective measurements of these same attributes. The sample of respondents was drawn from recreational moose hunters, who were asked to quantify their perceptions of six attributes at sites they had visited. Models estimated on these measurements could then be compared with models estimated using levels of the same attributes as measured by the Fish and Wildlife Service. Estimation showed that the models[4] based on perceived measures of environmental quality outperformed those based on objective measures.

Hanley et al. (1998) report results from a CE study of landscape and wildlife protection in Scotland, under the Environmentally Sensitive Areas scheme. This scheme offers payments to farmers in return for actions which protect or improve conservation features on their farms, within designated areas of the country. The CE was carried out using "Information Packs" which showed predicted landscape and wildlife change, should the policy continue, using photographs manipulated in Adobe Photoshop. Two CVM studies were carried out in tandem with the CE, using open ended and DC designs. Five landscape attributes were included in the CE design, and were all found to significantly influence choice. The implied ranking of these characteristics was identical to that produced by a simple ranking question. Finally, the programme value estimated with the CE was insignificantly different from the DC-CVM estimate, but both of these were considerably greater than the open-ended CVM figure.

Finally, Bergland (1997) used a variant of CE, involving the sequential elimination of alternatives, to value changes in agricultural landscapes in Norway. Respondents were presented with six different views of the same landscape, with features either added or removed. Respondents were asked to choose their most preferred landscape (each had a price tag attached to it), and then to discard this and choose their most preferred from the options remaining. This procedure was continued until all options had been chosen. An implied ranking, in WTP terms, of landscape features could then be derived. A notable feature of Bergland's study is that his choice data violate the IIA property, requiring an alternative estimation technique to be used.

There are several papers in the literature which make use of alternative conjoint analysis designs to CE (see, for example, Mackenzie 1993, on waterfowl hunting in Delaware; Johnson et al. 1996, on salmon preservation in the Pacific northwest; Foster and Mourato 1997, on wild birds and pesticide use in the UK; Roe et al. 1996, on Atlantic salmon fishery management; and Lareau and Rae 1987, on reducing odours from diesel-powered vehicles). These include contingent ranking exercises, and rated pair approaches. Since this paper is focused on the CE method, we do not summarize these papers here, but refer readers instead to the papers themselves.

4. An Example: Forest Landscapes in the UK

4.1. POLICY RELEVANCE AND SURVEY DESIGN

Public woodland generates a number of external benefits and costs. The Forestry Commission (FC) has, in previous years, commissioned work which estimated the biodiversity, recreational and carbon storage values of public forestry in the UK (ERM 1995; Willis and Benson 1989; Hanley and Ruffell 1993; Anderson 1990). The study on which the empirical part of this paper is based[5] was commissioned by the FC to estimate the external benefits of possible changes in landscape elements in public forests, due to changes in management. The relevant population of beneficiaries is taken to be the general public in the UK as a whole, and both CE and CVM approaches were used.

In discussions with FC landscape architects, a number of landscape attributes thought to be important were identified, and generic images of these produced. Focus groups were then conducted to allow feedback from the general public on:

– general attitudes to forest landscape;
– which attributes were important from the point of view of ordinary people;
– their attitude to paying for improvements in desirable attributes.

Demographic variables which appeared important in shaping attitudes were income, age, whether people “used” the forest, and whether they had children. Accordingly, the main survey collected information on all of these variables, as well as on residential location (both current and childhood). In terms of physical forest attributes, the shape of the forest (when viewed from a distance), felling scheme and species mix were important to respondents, with the latter dependent on season. Open space and edge effects were deemed much less important by the focus groups, and so were dropped from the design. Alternative bid vehicles were also tested, with access fees and self-financing being the most popular. However, since we wished to detract attention from recreational aspects and also estimate non-use values for landscape, income tax increases were chosen for the main survey.Visual material for the main survey was prepared by constructing photograph pairs or triples for each attribute (shape, species mix (spring, autumn and winter), and felling). In each pair/triple, only the attribute of interest was allowed to change. This was achieved by ‘doctoring’ electronic images using Adobe Photoshop, and printing them out again as photographs. A pilot survey of 160 people was carried out, using both CVM and CE, to further improve the questionnaires and photographs.

In the main survey, the CE main-effects design presented each respondent with four choice tasks. In each case, the respondent was asked to either choose option *A*, option *B* or the status quo. Options *A* and *B* were alternative forest designs, each bearing a price. The CE design incorporated three attributes only, each set at two levels: shape (straight edges versus organic edges); felling (large versus small scale clear felling) and species mix (evergreen only versus evergreen, larch and broadleaves mixture, with a equal proportion of spring, autumn and winter shots). In the CVM survey, respondents were asked to state their preference between each photograph in a pair/triple, and then to state their maximum WTP to move from their least preferred to most preferred image, assuming that landscape improvements were costly to produce. Respondents also tendered a WTP for an “ideal forest”, which incorporated each attribute at its most desired level, relative to status quo which set each at its least preferred level. The payment format used was an open-ended one. For a fuller description, see Entec (1997). Interviewing was undertaken in respondents’ houses, and interview took around 30 minutes to complete. The sample was chosen so as to be representative of the UK population, in terms of location, income, gender and age, on a quota sampling basis.

4.2. RESULTS

4.2.1. *The Choice Experiment*

Of the total of 284 respondents, a significant proportion refused to give their income levels and thus could not be used in the CE; whilst some respondents were only asked three choice questions, and so were also removed due to possible selection effects. These two problems reduced the sample down to 181 people. For each pair of descriptions, individuals could make one of three choices: choose option A, choose option B, or choose neither (i.e., prefer the status quo). Responses were first of all run through a programme which matched coded forest choice pairs to the descriptions of these choices, generating $(3 * 4)$ lines of data for all respondents receiving four pairs. We then used Limdep to estimate a mixed logit model describing the probability of a given choice being made as a function of its characteristics. Both linear and quadratic models were estimated, with the linear model performing best.

Table I. Logit model results

Variable	Coefficient	t-stat
Felling	0.42434	6.698
Shape	0.45737	7.345
Species	0.37396	6.083
Tax	–0.0329	–7.861
asc choice *A*	1.4096	2.27
asc choice *B*	1.6325	2.661
n = 724		
log L (0) –795.395		
log L (max) –513.2113		
chi-square (26) = 236.598		

Notes: ascA and ascB are Alternative Specific Constants.
Socioeconomic variables were included in the estimation, but their estimated values are not reported here. See text.

Using a linear indirect utility function, the following results were obtained for the characteristics in question (see Table I). As may be seen, all three forest characteristics are positively and significantly related to the probability of choosing an option, whilst tax is negatively and significantly related. The chi-square statistic allows us to reject the null hypothesis that none of the variables are significant determinants of choice at the 99% level. We also controlled for socioeconomic effects in the above equation, and found that whether the respondent has children,

Table II. Willingness to pay and implied rankings, choice experiment

Variable	Coefficient	Implied ranking	Incremental WTP
Felling	0.42434	2	£12.89
Shape	0.45737	1	£13.90
Species	0.37396	3	£11.36
Tax	–0.0329	*	*

Note: WTP is per household per year.

Table III. Comparing preferences for rural and urban respondents, choice experiment

3a) Rural dwellers:				
Attribute:	Coefficient	*t*-stat	Implied rank	Marginal WTP
Felling	0.372	3.3	3	£12.83
Shape	0.517	4.2	1	£17.82
Species	0.487	4.5	2	£16.79
Tax	–0.029	4.0	*	*
3b) Urban dwellers:				
Attribute:	Coefficient	*t*-stat	Implied rank	Marginal WTP
Felling	0.449	5.7	2	£12.82
Shape	0.461	6.2	1	£13.17
Species	0.334	4.3	3	£ 9.54
Tax	–0.035	6.7	*	*

whether the respondent lives in a rural area and whether the respondent has a rural childhood affected choices between forest pairs significantly at the 95% level. The parameter estimates for these socioeconomic variables are suppressed in what follows.

Willingness to pay to go from the less preferred to the most preferred level of each forest characteristic can be inferred from these results. An implied ranking of characteristics in terms of importance to the sample can also be derived (see Table II). As may be seen, the WTP terms for each attribute are quite similar to each other. Shape is the highest ranked attribute, with species diversity the lowest ranked. The implied WTP for an “ideal forest” with contoured edges, a diverse species and selective felling, over and above a forest with straight edges, evergreen monoculture and patch felling is therefore £38.15/household/year, if we assume a linear, additively-separable indirect utility function.

Table IV. Comparing preferences for users and non-users, CE sample

4a) Forest recreational users:				
Attribute:	Coefficient	*t*-stat	Implied rank	Marginal WTP
Felling	0.373	4.9	2	£13.32
Shape	0.462	6.3	1	£16.50
Species	0.348	4.8	3	£12.42
Tax	–0.028	5.8	*	*
4b) Forest non-users:				
Attribute:	Coefficient	*t*-stat	Implied rank	Marginal WTP
Felling	0.564	4.6	1	£11.05
Shape	0.462	3.6	3	£ 9.06
Species	0.466	3.7	2	£ 9.13
Tax	–0.051	5.7	*	*

Separate models were then estimated to compare the preferences of two groupings of respondents (i) rural versus urban households; and (ii) forest recreationalists versus those not using forests for recreation. For the rural/urban split, this gave 232 "choice observations" for the rural dwellers group, and 492 observations for the urban dwellers group. It is encouraging to note that in both models, all coefficients are significant and of the correct sign (Table III). As may be seen, preferences do differ between the two groups. We then estimated separate equations for those people who answered that they used forests for recreation (or had used in the past), as distinct from those who do not/have not. This gave 208 choice observations for non-users, and 516 observations for users. As Table IV shows, preferences again differ between the two groups. Non-users have lower valuations for landscape improvements than users, but these values are still positive.

4.2.2. *Comparing CE and CVM Results*

The attribute sets used in both experiments over-lap, so that valuations can be compared. As may be seen (Table V), the attribute values produced by the two methods are quite similar. The implied ranking of attributes is identical between the two methods, with shape being ranked first and species diversity third. Finally, note that the "ideal forest" bid from the CVM, whilst not directly comparable with the combined-attribute bid from the CE, is nevertheless quite similar to it (£38.15 in the CE, £29.16 in the CVM). This similarity of CE and CVM results may be compared to Adamowicz et al. (1996a) and Boxall et al. (1996). Note, however, that our study compares CE results with open-ended CVM data; this does not

Table V. Comparing CE and CVM bids

Attribute	CE sample		CVM sample	
	WTP	Rank	WTP	Rank
Felling: small scale rather than large scale	£12.89	2	£11.73[2]	2
Shape: organic rather than straight edges	£13.90	1	£12.75[2]	1
Species mix: most diverse rather than least diverse	£11.36[1]	3	spring: £11.24[2,3] autumn: £9.33[2,3] winter: –£1.75[2,3] overall: £7.52[4]	3
"Ideal forest"	∗		£29.16	
all attributes at preferred level	£38.15[5]		∗	

Notes:
[1]attributes shown in all three seasons.
[2]bids for minority preference included as negative bids for majority preference.
[3]using weights as follows: bid for evergreen only = –1, bid for evergreen + larch = 0; bid for evergreen + larch + broadleaves =1.
[4]overall average computed as [((£11.24 × 2) + (9.33) – (1.75))/4], i.e., counting spring as equal to summer.
[5]based on linear model.

share the same random utility basis as dichotomous choice CVM, and therefore we cannot treat the CE and open-ended CVM results to be theoretically equivalent. On the whole, using open-ended CVM designs gives lower WTP estimates than when using dichotomous choice designs (Bateman et al. 1995).

5. Conclusions and Future Directions

Choice experiments offer a promising new way forward in the field of environmental valuation. The approach is based on the notion that attributes of an environmental good can be used to understand the general trade-offs which an individual is willing to make. This is in contrast to CVM which focuses on a specific situation (specific change in an environmental good) and elicits a response unique to this case. Choice experiments offer some important advantages over CVM, principle of which is the ability to be able to estimate characteristic values for environmental goods. Whilst CVM can also estimate characteristic values, it is more cumbersome than CE in this respect. CE , in the context of recreational visits to outdoor sites, may be superior to CVM in terms of modelling substitution possibilities. The CE technique also possesses advantages over revealed preference approaches, in terms of avoiding co-linearity between attributes and being able to estimate non-use values. Finally, CE may be preferable to ranking-type valuation methods (e.g., Contingent Ranking), since the ranking of, say, five alternatives, is a more difficult mental task than pair-wise comparisons. In order to be consistent with economic models of choice and value, we need to know about choices. People may rank a group of alternatives but never actually choose any of them, given their budget constraints.

Principle problems in using the CE method are the often complex nature of the statistical/experimental design; and the selection of appropriate attributes and levels. The implied ranking of attributes is also dependent on the experimental design used, and accompanying materials. For example, in the forest landscapes study, the fact that shape was ranked above felling regime is partly a function of the actual photographs used, and the relative distances between the "good" and "bad" levels for each attribute.[6]

The application of choice experiments to environmental issues has been relatively recent, thus further testing of the approach in either use or non-use value cases is required. One major research need is to test whether CE perform better than CVM when benefits transfers are required, since CVM does not seem to do too well in this regard. Areas for further research also include the most appropriate method for the presentation of information in CE tasks, including the level of complexity respondents are exposed to and the degree of learning or fatigue that occurs whilst responding to choice tasks. Swait and Adamowicz (1997) outline an approach for modelling task complexity and its effects on choice probabilities. This study shows that the impact of complexity is context dependent, as is the degree of learning or fatigue that takes place.

An issue that affects the CE approach is the degree to which stated choices can be externally validated. In the case of recreation site choice, there is considerable evidence that revealed and stated preference models can generate similar preference patterns (when scale or variance differences between the data types are taken into account): see Adamowicz et al. (1994) for some evidence on this point. However, in cases of less familiar choices, or non-use values, such tests of external validity will be more difficult. This is directly equivalent to the calibration/validation problems in CVM as applied to unfamiliar goods and/or non-use values. It may even be the case that the set of attributes that are relevant to users of a resource may be different from the set which is relevant to those that derive non-use values from that resource. This would imply the need for different experimental designs for the two types of value. Finally, a topic that is receiving attention in choice modelling, in models employing revealed and/or stated preference data, is the treatment of heterogeneity in the population or sample. Heterogeneity can be addressed using latent class approaches or using heterogeneous model estimators like the random coefficient probit and logit models (Swait 1994).

Notes

1. The research on which this paper is based was carried out as part of a Forestry Commission-funded project on the economic benefits of improving forest landscapes in the UK. We thank the Commission for this funding, members of the Steering Group for comments and the other members of the study team (Entec UK and Wood-Holmes marketing), especially Ken Taylor. We also thank Ian Hodge, Olvar Bergland and Rich Ready for comments on an earlier draft presented at the Norwegian Agricultural University, Aas; and seminar participants at the universities of Edinburgh, Nottingham and East Anglia. All views reported in this paper, however, are ours alone.
2. In Foster and Mourato (1997) their data set passes the IIA test, but the reverse was found by Bergland (1997). If choices violate IIA, then alternative approaches must be taken (see, for example, McFadden and Ruud 1994).
3. As Louviere (1995) points out, . . . "there is no "plain vanilla" conjoint approach, since conjoint analysis seems to be what conjoint analysts do, and each . . . applies the technique differently . . . it's behavoural foundations are rarely discussed . . . ".
4. Both revealed and stated preference data were collected, and joint models also estimated.
5. The study team comprised Entec, the Environmental Economics Research Group (University of Stirling), of which Hanley was Director at the time of the study, and Wood-Holmes Marketing.
6. Thanks to Ian Hodge for pointing this out.

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