Attribute Selection in Environmental Choice Modelling Studies: The Effect of Causally Prior Attributes*

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Research Report No. 7
October, 1998

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*An earlier version of this paper was presented at the conference of the Australian and New Zealand Society for Ecological Economics (ANZSEE), 17-20 November, 1997, Melbourne.
Choice Modelling Research Reports are published by the School of Economics and Management, University College, The University of New South Wales, Canberra 2600 Australia.

These reports represent the provisional findings of the research project ‘Using Choice Modelling to Estimate Non-Market Values’.

The project is being funded by the Land & Water Resources Research and Development Corporation and Environment Australia under their joint program on the conservation and management of remnant vegetation. Support for the project is also being provided by the Queensland Department of Primary Industries, the Queensland Department of Natural Resources, the New South Wales National Parks and Wildlife Service and the New South Wales Environment Protection Authority.

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Abstract

When selecting attributes in environmental CM studies, preference should be given to those attributes that are demand-relevant, policy-relevant, and measurable. The use of these criteria will often result in a short list of environmental attributes of which some are causally related. The inclusion of causally-related attributes may stimulate some respondents to seek to understand the causal relations among attributes in order to assign greater meaning to the alternatives, and potentially, simplify the decision making process. This may have implications for the weights they assign to each of the attributes when identifying the preferred alternatives, and subsequently, implicit prices and/or welfare estimates.

A test of the effect of including a causally prior attribute pertaining to ecosystem health on parameter estimates, implicit prices and welfare estimates is conducted. Two questionnaires are developed, one with a causally prior attribute included and one without. Limited support is found for the hypothesis that including causally prior attributes, such as area of unique ecosystems, can affect the importance of downstream attributes, such as loss of endangered species. Whilst no significant difference in the attribute taste vectors is detected, the implicit value of a single endangered species falls by 34 per cent when the ecosystem attribute is included. Importantly, however, estimates of compensating surplus do not differ significantly across the two treatments for a given policy package. This implies that to the extent that the inclusion of a causally prior ecosystem attribute reduces the implicit prices for one or more of the downstream attributes, the associated loss in utility is approximately offset by the utility associated with the new attribute.
1 Introduction

The use of stated preference (SP) non-market valuation methods such as the Contingent Valuation Method (CVM) is becoming increasingly popular in the environmental context. The focus of this Research Report series is an emerging, alternate SP technique known as choice modelling (CM).

Whilst applications of the discrete choice CVM require respondents to choose between a base option and a single alternative, CM employs a repeated measures approach. Respondents are typically presented with six to ten choice sets, each containing a base option and two or three alternatives. They are required to indicate which option they prefer in each choice set. The levels of the attributes characterising the different choice set options are varied according to an experimental design, permitting estimates of the relative importance of the attributes describing the options to be obtained. Rather “than being questioned about a single event in detail, as in CVM analysis, subjects are questioned about a sample of events drawn from the universe of possible events of that type” (Boxall, Adamowicz, Swait, Williams and Louviere, 1996, p244).

Issues pertaining to scenario construction and selection of the vehicle (tax increase, higher prices etc) through which payment is to be made apply to CM as they do with CVM.

CM offers several potential advantages over CVM, including the ability to break down the overall welfare implications of a policy into the implications associated with each of a number of outcomes, or attributes. By including substitute goods within the choice sets, respondents to CM questionnaires are also explicitly required to consider substitutes when formulating their responses. Another potential advantage of CM is the ability to estimate the welfare implications of multiple mutually exclusive policy options within the one survey.

CM is not without its challenges and limitations. Being a relatively new method of environmental valuation, there is considerable scope to increase our understanding of many of the issues involved in the conduct of these studies. The extent to which biases occurring in the CVM context also affect CM studies is not well understood. One would also expect a new approach to bring with it a number of unique challenges and problems. For example, CM presents challenges in experimental design and discrete choice modelling that do not arise to the same degree with CVM. Issues also arise in relation to the number of alternatives that should be included in each choice set, the labelling of alternatives, and the number and nature of attributes used to define the alternatives.

One such issue, the selection of attributes, is the focus of this particular Research Report. It has been argued in a previous Research Report in this series that when selecting attributes in environmental CM studies, preference should be given to those attributes that are demand-relevant, policy-relevant, and measurable (Blamey, Rolfe, Bennett and Morrison, 1997). The use of these criteria will often result in a short list of environmental attributes of which some are causally related. For example, the attributes ‘endangered species lost’ and ‘non-threatened species lost’ may be perceived to be causally ‘downstream’ of attributes such as ‘loss in area of native vegetation’. In this case, the CM practitioner has to decide whether to include all three attributes, just the two ‘downstream’ attributes, or just the ‘upstream’ attribute.

The decision to include or exclude certain attributes is often far from clear cut. This may be particularly the case in environmental studies where respondents often have little familiarity with what are very

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1 The research reported in this paper was funded by the the Land and Water Resources Research and Development Corporation (LWRRDC), Environment Australia, Queensland Department of Primary Industries (QDPI) and the Queensland Department of Natural Resources (QDNR). The authors thank Wiktor Adamowicz for his useful feedback regarding an earlier version of this paper.

2 This approach can be more restrictive than the more general framing statements typically included in CVM studies, and is best suited to cases where a small number of relatively close substitutes are separable from other goods. CVM style framing statements can be included in CM questionnaires to give a more comprehensive and appropriate frame.
complex issues. Among the factors to be considered when selecting from a short-list of attributes are task complexity, the plausibility and meaning of alternatives, and the strategies respondents are likely to employ when formulating their responses. The inclusion of causally related attribute sub-sets raises questions regarding each of these issues.

Depending in part on how the CM exercise is framed, the inclusion of causally-related attributes may stimulate some respondents to seek to understand the causal relations among attributes in order to assign greater meaning to the alternatives, and potentially, simplify the decision making process. This may have implications for the weights they assign to each of the attributes when identifying their preferred alternatives, and subsequently, implicit prices and/or welfare estimates. Such response patterns have been detailed in two other Research Reports in this series (Blamey, Rolfe, Bennett and Morrison 1997 and Morrison, Bennett and Blamey 1997).

Unfortunately, these strategies are not always desirable from a practitioner’s perspective, where respondents are requested to view the attributes as final outcomes. This raises the question of whether causally-related attributes should be included in choice sets, and if so, how they should be presented and explained to respondents. This question provides the focus of this Research Report. Specifically, the effects of including a causally prior attribute pertaining to ecosystem health on parameter estimates, implicit prices and welfare estimates are tested. To this end, two questionnaires are developed, one with the causally prior attribute included and one without. The tests are considered in the context of the value of remnant vegetation stands in the Desert Uplands of Central Queensland, the details of which were presented in a previous Research Report in this series (Rolfe, Blamey and Bennett 1997).

This Research Report is structured as follows. The theoretical basis of CM is briefly reviewed in Section 2, and issues of causality and meaning are considered in more detail in Section 3. The application involving remnant vegetation in the Desert Uplands of Central Queensland is described in Section 4, and the methods and hypotheses in Sections 5 through 7. Results are presented in Section 8, and discussed briefly in the final section.

2 Theoretical Basis of Choice Modelling

Choice modelling has its origin in conjoint analysis, information integration theory in psychology and discrete choice theory in economics/econometrics (Louviere, 1988). Conjoint analysis has been widely used in market research, and involves “decomposition into part-worth utilities or values of a set of individual evaluations of, or discrete choices from, a designed set of multiattribute alternatives” (Louviere, 1988, p93). As such, these approaches have foundations in Lancaster’s (1966, 1991) modern consumer theory (see Blamey et al, 1997, for a discussion).


Both CM and the dichotomous-choice CVM have their theoretical bases in random utility theory (RUT). According to RUT, the ith respondent is assumed to obtain utility \( U_{ij} \) from the jth alternative in choice set C. \( U_{ij} \) is held to be a function of both the attributes of the alternatives (\( X_{jk} \) representing the kth attribute value of the jth alternative) and characteristics of the individual, \( S_i \). \( U_{ij} \) is assumed to comprise a systematic

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3 Several different conjoint paradigms exist, differing in terms of the response modes employed, methods of analysis and interpretation of results (Louviere, 1988). Morrison, Blamey and Bennett (1996) discuss the different paradigms in detail.
component $V_{ij}$ and a random component $e_{ij}$. Whilst $V_{ij}$ relates to the measurable component of utility, $e_{ij}$ captures the effect of omitted or unobserved variables. We thus have

$$U_{ij} = V_{ij}(X_{ij}, S_i) + e_{ij} \quad (i)$$

Respondent $i$ will choose alternative $h$ in preference to $j$ if $U_{ih} > U_{ij}$. Hence:

$$P_{ih} = \text{Prob} \left( U_{ih} > U_{ij} \right) \text{ for all } j \in C, j \neq h$$

$$= \text{Prob} \left( V_{ih} - V_{ij} > e_{ij} - e_{ih} \right), \text{ for all } j \in C, j \neq h \quad (ii)$$

The $e_{ij}$ for all $j$ in $C$ are typically assumed to be independently and identically distributed (IID) and in accordance with the extreme value (Gumbell) distribution. This gives rise to the multinomial logit model, commonly employed in discrete choice modelling, of which the binary logit used in CVM studies is a special case:

$$P_{ih} = \frac{\exp[\lambda V_{ih}]}{\sum_{j \in C} \exp[\lambda V_{ij}]} \quad (iii)$$

where $\lambda$ is a scale parameter, which is inversely proportional to the variance of the error term, and commonly normalised to 1 for any one data set (Ben-Akiva and Lerman, 1985). An estimated linear-in-parameters utility function for the $j$th alternative often takes the following form:

$$V_j = \text{ASC}_j + \beta_1 X_{1j} + \beta_2 X_{2j} + \ldots + \beta_k X_{kj} + \gamma_1 (S_1 \ast \text{ASC}_j) + \ldots + \gamma_m (S_m \ast \text{ASC}_j) \quad (iv)$$

where there are $n$ attributes with generic coefficients across alternatives, and $m$ individual-specific variables multiplied by an alternative-specific-constant (ASC). The ASCs capture the mean effect of the unobserved factors in the error terms for each alternative. This provides a zero mean for unobserved utility and causes the average probability of selecting each alternative over the sample to equal the proportion of respondents actually choosing the alternative. Socioeconomic and attitudinal variables can be included by interacting them with the alternative-specific constants, as shown, and/or the attributes (not shown).

The inclusion of ASCs helps mitigate inaccuracies due to violations in the assumption of independence of irrelevant alternatives (IIA) (Train, 1986). This assumption, which arises from the above-mentioned IID assumption, requires that the ratio of the choice probabilities for any two alternatives be unaffected by the addition or removal of alternatives. This is equivalent to assuming that the random error components of utility are uncorrelated between choices and have the same variance (Carson, Louviere, Anderson, Arabie, Bunch et al, 1994). Violations of the IIA assumption render the MNL model inappropriate.

Another way of circumventing IIA violations is to allow for correlations among the error terms within different groups or classes of alternatives by estimating a nested logit model (McFadden, 1978, Dagunzo and Kusnic, 1993). In a two level nested logit model, the probability of an individual choosing the $h$th alternative in class $r$ ($P_{hr}$) is represented as:

$$P_{hr} = P(h|r)P(r) \quad (v)$$

where $P(h|r)$ is the probability of the individual choosing the $h$th alternative conditional on choosing the $r$th class of outcome, and $P(r)$ is the probability that the individual chooses the $r$th class. Following Kling and Thomson (1996):

$$P_i(h|r) = \frac{\exp[V_{hr}/\alpha_r]}{\exp[V_{hr}/\alpha_r]} \quad (vi)$$
\[ P_i(r) = \frac{\exp[\alpha_r I_r]}{\sum_{k=1}^{nR} \exp[\alpha_k I_k]} \]

where

is referred to as the inclusive value. This is a measure of the expected maximum utility from the alternatives associated with the rth class of alternatives. The coefficient of inclusive value \( \alpha \) measures substitutability across alternatives. When substitutability is greater within rather than between alternatives, \( 0 < \alpha < 1 \). In this case, respondents will shift to other alternatives in the branch more readily than they will shift to other branches (Train, McFadden and Ben-Akiva, 1987). The popularity of the nested logit model is in part due to the way in which nested decision structures lend themselves to behavioural interpretations.

Welfare estimates are obtained in CM studies using the following general formula described by Hanemann (1984):

\[ W = -\frac{1}{\mu} \left[ \ln \left( \sum_{i \in C} e^{V_{i0}} \right) - \ln \left( \sum_{i \in C} e^{V_{i1}} \right) \right] \]

where \( \mu \) is the marginal utility of income, \( V_{i0} \) and \( V_{i1} \) represent the indirect observable utility before and after the change under consideration, and \( C \) is the choice set. In CM, the coefficient of the monetary attribute is taken as an estimate of \( \mu \). Changes in \( V_{i0} \) or \( V_{i1} \) can arise from changes in the attributes of alternatives or the removal (or addition) of alternatives altogether. For example, in recreational site studies where alternatives are substitutes in consumption, the removal of an alternative from the choice set might correspond to a site closure, which one would expect to result in a welfare loss. When alternatives are substitutes in ‘production’, for example, when a single solution has to be chosen from a set of feasible solutions, the removal of alternatives can be used to estimate selection probabilities and welfare implications based on different choice set configurations.

When the choice set includes a single before and after policy option, equation (ix) reduces to:

\[ W = -\frac{1}{\mu} \left[ \ln(e^{V_{i0}}) - \ln(e^{V_{i1}}) \right] \]

\[ = -\frac{1}{\mu} [V_{i0} - V_{i1}] \]

In the case of changes in a single attribute, this further reduces to \( -\beta / \mu \) when a linear in parameters utility function is employed. This is equivalent to calculating the ratio of marginal utilities for the attribute in question and the monetary attribute, or the marginal rate of substitution (MRS) (Hensher and Johnson, 1981). Kling and Thomson (1996), Herriges and Kling (1997) and Choi and Moon (1997) consider the application of (ix) in the nested logit case.

3 Meaning and Causality in CM Tasks

Consideration of the effect of including causally-related attributes in choice sets raises questions regarding the way respondents categorise and assign meaning to CM tasks as a whole, and also alternatives within choice sets. Research in cognitive social psychology indicates that the way individuals categorize
situations has a critical bearing on the way they organise and structure their decisions\(^4\). Different categorisations tend to result in different information filtering, organisation and integration (Eiser, 1980). Categorization also influences the beliefs, attitudes and personal and social norms that are operative in a given context (Leyens and Codol, 1988).

Observations made by the authors when focus grouping CM questionnaires indicate that participants sometimes have difficulty categorising either the task as a whole, or individual choice sets and alternatives within the task. In particular, they often try to establish the meaning of alternatives and/or differences between alternatives and the status-quo or do-nothing option.

In such cases, the researcher must devise appropriate stories and frames to “suspend disbelief” and allow subjects to categorize and assign meaning to the task in the desired way. Whilst this approach offers considerable promise, it is unlikely that all disbelief will be suspended as a result. The result is that some respondents may become confused about the meaning of alternatives and/or the task requirement. Consequently, they may seek clarification by increasing the effort they devote to the task. Alternatively, they may reduce their effort, for example, by giving up altogether, or adopting simplified decision strategies or heuristics. Examples of the latter include the use of causal strategies and biases toward the status quo.

**Causal Strategies**

Respondents to CM questionnaires may use a variety of strategies when formulating their responses. In some cases, respondents may seek to simplify their decisions by limiting the number of attributes and/or alternatives to be considered and rationally processing these (Reber, 1985). According to Simon’s (1955) notion of ‘bounded rationality’, individuals will omit from consideration any information for which the marginal processing costs exceed the expected returns.

One type of strategy which may be particularly relevant here is the causal heuristic, sometimes referred to as the causal schema (Tversky and Kahneman, 1982, Einhorn and Hogarth, 1985, Heider, 1958)\(^5\). As Tversky and Kahneman (1982, p117) observe:

> It is psychological commonplace that people strive to achieve a coherent interpretation of the events that surround them, and that the organisation of events by schemas of cause-effect relations serves to achieve this goal. The classic work of Michotte (1963) provided a compelling demonstration of the irresistible tendency to perceive sequences of events in terms of causal relations, even when the perceiver is fully aware that the relation between the events is incidental and that the imputed causality is illusory.

Kelley (1972) originally proposed the notion of a causal schema, defining it as “a conception of the manner in which two or more causal factors interact in relation to a particular kind of effect. A schema is derived from experience in observing cause and effect relationships... It enables a person to perform certain operations with limited information and thereby to reach certain conclusions...”(p2).

Einhorn and Hogarth (1985, p313) observe that “one must have some hypothesis or theory for selecting relevant from irrelevant variables. Indeed, relevance can only be understood in relation to some model

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\(^4\) In psychology, the term ‘categorization’ refers to the cognitive process whereby people group a set of objects that have one or more characteristics in common. This is similar to the notion of a schema, which is a cognitive structure that represents organized knowledge about a given concept or stimulus, and which influences perception, memory and inference. By contrast, a heuristic is a cognitive short cut that reduces complex problem-solving to more simple judgemental operations. Their use is typically automatic (Hewstone, Stroebe, Codol and Stephenson 1988, p445-457).

\(^5\) A heuristic is a cognitive short-cut that people use to make judgements, often involving uncertain events, and hence probabilities.
(usually implicit) of what generates the variable[s]” in question\(^6\). Perceptions of technical redundancy (Lancaster, 1991) may have an influence on the weights individuals attach to different attributes when making choices. Einhorn and Hogarth (1983) argue that individuals are less likely to use erroneously causal schemas when alternative explanations exist. However, there will always be some individuals who sacrifice accuracy for a reduction in effort.

In the CM context, some respondents may consider causal relations among attributes when assessing both the meaningfulness of alternatives and the relative importance of the attributes. Alternatives considered to have implausible combinations of environmental and/or other attributes may be dismissed, or at a minimum, discounted\(^7\). Some respondents may also assign greater weight to attributes of a more fundamental, causally prior, nature.

Three main ways of reducing the use and/or influence of causal strategies exist. The first involves reframing the choice exercise so that respondents no longer employ causal strategies. As noted above, respondents are less likely to use such strategies when alternate explanations exist. The more a CM task and context can be designed to fit respondents’ schemas of correlation and causality, or at least suspend any disbelief, the lower their need to assign meaning to alternatives through the use of potentially problematical judgements and choices. The onus is on the researcher to identify problematic strategies during pre-testing and devise ways of addressing them. For example, respondents might be told that although some combinations of outcomes may appear a little strange, they are in fact quite possible. In some cases, it may be possible to provide one or two examples. Another approach is to request that respondents not consider the meaning of alternatives. Instead, they are to simply take each outcome at face value. This approach is more likely to succeed when an explanation can be offered as to why this is a sensible thing to be doing.

The second approach is to combine two or more attributes together to form a single composite attribute. Only the latter is treated as a factor when developing the experimental design. Suppose we generate a three level composite attribute to represent the correlated effects of ‘loss in endangered species’ and ‘loss in area of native vegetation’. One level in the design could be assigned to 20% loss in endangered species and, say, 30% loss in area of native vegetation. Another could be assigned to 40% loss in endangered species and 50% loss in area of native vegetation. Whilst the two sub-attributes might be presented as two correlated attributes in the choice sets, they are developed from a single two-level factor in the design. Unfortunately, the utility attributable to the sub-attributes cannot be separated with this approach, since the attribute now takes on a qualitative status. However, in some cases, it may be possible to maintain orthogonality among the sub-attributes, thereby enabling them to be modelled separately. This approach can complicate experimental designs and will not always be feasible, particularly when more than two sub-attributes are involved.

The third approach is to select attributes from only one level of the cause-effect hierarchy. This means omitting either the causally upstream or downstream attributes from the exercise altogether. Whilst this approach is probably the simplest to implement, the possibility of omitted variable bias remains.

**Status-Quo Biases**

People tend to categorize situations based on their similarities to other situations with which they have experience. Whilst CM respondents can be expected to have some familiarity with community questionnaires and the type of questions typically contained in these questionnaires, they are likely to be less familiar with the type of task requirement presented in CM questionnaires. In contrast to CVM

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\(^6\) Einhorn and Hogarth (1985, p323) also note that “a significant feature of causal/diagnostic thinking is the remarkable speed and fluency that people seem to have for generating explanations and accommodating discrepant facts into expanded hypotheses”.

\(^7\) This problem is not expected to be common in CVM studies, where the alternatives presented to respondents are policy-relevant and often based on the results of ecological modelling. However, it is expected to be more common in CM studies, where the combinations of outcomes are not policy-relevant, instead being generated using orthogonal (or near orthogonal) experimental designs.
questionnaires, which can be designed to have similarities with referenda and simple community questionnaires. CM questionnaires present a set of questions that, as a whole, are relatively unfamiliar to individuals. Focus-group participants sometimes ask questions such as: ‘Why are the questions all so similar’, ‘Why do you need so many questions’, and ‘If you are trying to work out which features are important, why don’t you just ask us in a single question?’.

Whilst framing strategies can potentially be devised to offset or reduce such perceptions, a degree of respondent confusion can be expected to remain. The result can be greater use of rules of conservatism and a bias toward the status-quo option (Ritov and Baron, 1992). Adamowicz et al (1988) report evidence of status-quo biases in a CM study of passive use values associated with a caribou habitat program. Explanations offered for a significant and negative ASC associated with moving away from the status quo include the task being too complex, respondent uncertainty regarding the trade-offs they are willing to make, and protest responses. Opaluch and Segerson (1989) suggest that respondent ambivalence in CVM surveys may lead to greater use of rules of conservatism and lexicographic responses. One might expect confusion to have similar implications in both CVM and CM studies.

4 Hypotheses

Our main objective in this paper is to consider the effect of including an environmental attribute within choice sets that respondents may perceive to be causally upstream of other included attributes. Two questionnaires are required to examine these effects, one containing the causally prior attribute, and one excluding it. In the version containing the causally prior attribute, the above-mentioned framing approach was employed in an attempt to reduce the use of causal schemas. Hence, the comparison involves the first and third approaches outlined in the previous section. Each questionnaire is administered to a separate random sample of individuals.

The first hypothesis involves a consideration of the effect of including a causally prior environmental attribute on the overall parameter vectors. The nature of the changes is not specified:

H1a: Inclusion of a causally prior attribute changes the behavioural relationship between the dependent variable and the common independent variables.

A feature of the MNL model is that parameter estimates are confounded with a scale parameter $\lambda$, which is inversely related to the error variance. The scale parameter cannot be estimated for any one data set, with only the ratio of scale parameters from different data sets (or segments) being estimable. The addition of an attribute may increase the variance of the error term due to the extra cognitive burden of the task. Alternatively, the variance may decrease if inclusion of an attribute leads to greater homogeneity in choice processes, for example, due to a more meaningful interpretation of alternatives and/or widespread use of the causal heuristic.

Any consideration of H1a thus first requires differences in the scale parameter to be taken into account. Accordingly, the first hypothesis is redefined to involve a consideration of differences in the underlying $\beta$ vectors when scale factors are permitted to vary between data sets:

H1b: $\beta^1 = \beta^2$

where $\beta^1$ and $\beta^2$ are the true taste parameter vectors corresponding to data sets 1 and 2, and the estimated parameters are $\hat{\beta}^1 = \lambda^1 \beta^1$ and $\hat{\beta}^2 = \lambda^2 \beta^2$ respectively. This amounts to testing:

8 Obviously, the way in which respondents categorize a CM task can to some extent be influenced by the way it is introduced in the questionnaire. Whilst the effect of alternate framing statements and other design features can be explored when piloting and focus grouping questionnaires, the extent to which such endeavours can eliminate respondent confusion is unclear.
\[ H1b': \beta^{2*} = \lambda^{12} \beta^1, \]

where \( \lambda^{12} \) represents the ratio of scale factors. The proportionality underlying this hypothesis can be visually assessed by estimating models for the two treatments and plotting the resultant taste parameter vectors against each other. If the two parameter vectors appear equal up to a positive constant of proportionality, the main differences may be due to scale rather than taste differences. Precise estimates of \( \lambda^{12} \) can be obtained by stacking data sets \( X_1 \) and \( X_2 \) and conducting a one-dimensional grid search over different values of \( \lambda \) such that \( X_1 \) is transformed to become \( \lambda X_1 \). The correct value of \( \lambda^{12} \) is that which maximises the log-likelihood for the MNL model estimated over the stacked data with transformed \( X_1 \) (Swait and Louviere, 1993). A value of \( \lambda^{12} \) less than one implies that a lower scale parameter, and hence larger random noise component, is applicable to data set 1. When no scale difference exists between the two data sets, \( \lambda^{12} \) equals one.

A likelihood ratio test is used to test whether \( H1b' \) can be rejected. Following Swait and Louviere (1993), the test statistic is:

\[ LR_{1b'} = -2[\text{LogL}_{\lambda^{12}} - (\text{LogL}_{X_1} + \text{LogL}_{X_2})] \]

where \( \text{LogL}_{\lambda^{12}} \) is the log-likelihood obtained from the stacked \( \lambda^{12}X_1 \) and \( X_2 \) data sets, and \( \text{LogL}_{X_1} \) and \( \text{LogL}_{X_2} \) are the log-likelihoods corresponding to separate estimations on \( X_1 \) and \( X_2 \). This test statistic is asymptotically chi-square distributed with \( C-1 \) degrees of freedom, where \( C \) is the number of parameters common to the two models. The additional degree of freedom in the restricted model is associated with estimation of the scale parameter.

Whilst \( H1b' \) can in principle be applied to the entire parameter vector or any subset thereof, in practice, the test is usually restricted to the terms not involving the ASC. Including the ASC terms represents a stringent requirement, requiring not only that the response to the attributes be proportional across the two data sources, but also that the aggregate shares be equal (Swait, Louviere and Williams, 1994). It can also be difficult to develop meaningful hypotheses and interpretations regarding the ASC terms, as they relate to unobserved effects.

In the event that \( H1b' \) is rejected for a given set of parameters, it is desirable to try and isolate the source of the violation. This can be done by postulating sources of the violation, for example by examining the plot of coefficient vectors, and allowing these parameters to differ between data sets. \( H1b' \) is then repeated for the component of the parameter vectors subject to the equality restriction.

The second hypothesis is targeted towards the detection of differences in the marginal rates of substitution (MRS) between attributes across the two data sets. Of particular interest are differences involving the monetary attribute, as these are most relevant to welfare estimation. To the extent that inclusion of a causally prior attribute results in use of a causal heuristic, we would expect respondents to assign lower value to downstream attributes, for example, impact on endangered species. Because the scale factors cancel when dividing coefficients, estimates of MRS are essentially independent of differences in error variances. Specifically, \( H2 \) is proposed.

\[ H2: \text{Inclusion of a causally prior attribute reduces the MRS between the downstream environmental attributes and money.} \]

Rejection of \( H1b' \) and \( H2 \) would imply that the causal heuristic is not the main factor driving a difference in parameter vectors. The method outlined by Poe, Severance-Lossin and Welsh (1994) and Poe, Welsh and Champ (1997) is used to test \( H2 \). The Krinsky and Robb (1986) procedure is first used to simulate the distribution of the MRS measures. For each version of the questionnaire, multiple parameter vectors are drawn randomly from a multivariate normal distribution with the mean and variance-covariance matrix of the sample logistic distribution. Each of these vectors is used to calculate the MRS’s of interest. Following Poe et al (1994), the simulated MRS’s are then paired across the two treatments and differences taken. Finally, a one-sided approximate significance level is estimated by calculating the proportion of the
differences with the hypothesised sign.

The third hypothesis pertains to differences in compensating surplus for given policy changes. The equality of welfare estimates across the two treatments is tested. It is important that this hypothesis be considered as it is conceivable that the addition of the causally prior attribute simply redistributes the source of the utility in terms of the attribute part worths and/or the ASC’s. As noted in Section 3, including this attribute may shift respondents’ attention from the downstream attributes to the upstream attributes. The overall utility of a given policy option could conceivably remain unchanged if a utility decrease with respect to the downstream attributes is approximately offset by an increase in the utility derived from the upstream attribute. To test this hypothesis, the Poe et al (1997) procedure is applied to estimates of compensating surplus obtained using equation (x). The third hypothesis is thus:

H3: Inclusion of a causally prior attribute results in different welfare estimates for specified changes in remnant vegetation retention rates.

Because this test requires specification of the attributes of the proposed policy option, including the causally prior attribute, results may be sensitive to the assumed level of the prior attribute. A further caveat is that interactions between the causally upstream and downstream attributes are not tested in this paper, as the experimental design employed in this study did not permit these interactions to be properly estimated. Future research might consider, for example, whether the effect of downstream attributes on the odds of an alternative being chosen depends on the level of the upstream attribute.

The final two hypotheses relate to respondent confusion. Respondent confusion is expected to be associated with a bias toward the do-nothing option. However, it is not clear in which of the two treatments confusion will be higher. On the one hand, the primary effect of including the additional attribute may be to increase cognitive burden and thereby confusion. On the other hand, the addition of a causally prior attribute may make the alternatives more meaningful for respondents, thereby reducing confusion. Accordingly, our final hypotheses are specified as follows:

H4a: Confusion has a significant negative affect on the utility of environmental improvement options; and

H4b: Self-reported confusion is lower when a sixth, causally prior attribute, is included in choice sets.

H4a involves examining the effect of respondent confusion on the tendency to choose the status-quo option. Confusion-induced status quo bias can be tested by multiplying the ASC for the environmental improvement options by self-reported confusion. An advantage of parametising specific status quo effects within the utility functions is that different values of these variables can be plugged into equations (ix) and (x) to obtain different welfare estimates for different levels of confusion or protest.

H4b involves testing for equality of means in self-reported confusion, across the two treatments, using a paired t-test.

The above hypotheses are explored in the context of a CM study directed at estimating the non-use values associated with increased retention of remnant vegetation in the Desert Uplands region of Central Queensland, Australia.
5 Case Study

The Desert Uplands is one of thirteen terrestrial biogeographic regions of Queensland, Australia, covering some 6,881,790 hectares (4% of Queensland). The region is essentially a band of scattered woodland country between the open grasslands of the arid western plains and the semi-arid to sub-humid brigalow (Acacia harpophylla) country to the east. The region is relatively unproductive for pastoral and agricultural purposes compared to other regions in the south and east of Queensland. This is because of its relatively low rainfall and poor soils, and its vegetation which is reasonably unpalatable to domestic stock. One reason why the term ‘desert’ is attached to the area is because spinifex (Triodia spp.), a grass common to the drier areas of Australia, is a major grass species in the region.

The region is almost exclusively used for pastoral purposes. Cattle are bred and fattened for beef production over much of the region, and sheep are also run in some areas. Pastoralists have been attempting to increase the carrying capacity of their land by a variety of methods, including the clearing of trees and the introduction of non-native grass species. Initially these developments were limited to patches of more fertile soils. The region now has one of the highest clearing rates in Australia, with between 4 and 8% of many broad country types being cleared between 1992 and 1995 (McCosker and Cox 1996).

Landholders must gain permission to clear trees from the State Government through the Department of Natural Resources. In issuing the permits for broadscale tree clearing, the State Government policy calls for a balance between the benefits of increased productivity (most of which accrue directly to the landholders) against the environmental costs of diminished vegetation cover (which are more broadly spread across the regional and national communities). It is these environmental costs that the CM application described below is directed at estimating.

The Queensland Government has recently been revising its tree clearing policies, with the result that vegetation communities that are endangered or vulnerable (whether through past clearing activities or limited initial occurrence) are now protected. Other vegetation communities can be cleared to 20% of their original extent on individual properties, with 30% of each vegetation type to be retained across the region. The CM exercise is designed to estimate the benefits of retaining 30% of native vegetation rather than the 20% currently allowed.

6 Focus Grouping and Questionnaire Design

Two sets of focus groups were conducted in developing the survey instruments. The first set, involving two groups in Brisbane and a further two at Emerald in the local region, was conducted with the dual purpose of identifying the key consumer decision parameters and trialing an initial draft questionnaire. The second set of two groups undertaken in Brisbane concentrated on refining a revised questionnaire.

The key decision parameters identified in the first set of focus groups fell into three main categories: economic implications of tree clearing restrictions; impacts on endangered and other species; and impacts on ecosystems including land degradation. Following a consideration of the policy-relevance and measurability of the different candidate attributes, the six attributes listed in Table 1 were selected. The levels assigned to the attributes were chosen such that the resultant attribute-space would encompass the vast majority of policy-relevant tree clearing options.

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9 Information regarding the ecological and economic effects of different tree clearing options in the Desert Uplands is extremely limited. Information that could be gained was obtained from a variety of sources, including previously published research (summarised in an earlier Research Report in this series - Rolfe, Blamey and Bennett, 1997) and consultation with experts. The high level of uncertainty regarding the levels of attributes, such as impact on endangered species, meant that the range of levels chosen was more extreme than one would expect to be the case with most policy options.
The two main versions of the questionnaire were equivalent with the exception that the causally prior ‘ecosystem’ attribute was omitted from one. This addresses the question of whether causally upstream attributes should be included in choice sets when focus groups indicate they are important to individuals. On one hand, such attributes should be included when they are both demand-relevant, policy-relevant and measurable. In the present study, this rationale would probably see the ecosystem health attribute being included.

On the other hand, including causally related variables can be expected to cause a degree of redundancy in some of the attributes, and may complicate interpretation of results. A key question is whether the causally prior attribute has importance independent of its influence on other included attributes. Focus group observations did indicate a tendency of participants to assign additional weight to the upstream ecosystem attribute. A laddering style of questioning was consequently used to explore this question. Those participants viewing the ecosystem attribute as important were asked why they thought so. A succession of ‘but why is that important’ questions followed until what could be considered to be fundamental objects of value were elicited. In the vast majority of cases, the fundamental value of ecosystems in the Desert Uplands was perceived to involve jobs and threatened and non-threatened species. However, there was some indication that ecosystem health is valued beyond such objects. For example, a small number of participants made statements that appeared to relate to the value of future scientific discoveries (quasi-option value). There was also a number of references to tourism that appeared to involve concerns not attributable solely to jobs, income, and threatened and non-threatened species (for example, altruism towards potential tourists).

Overall, ecosystem health appeared to represent somewhat of a ‘catch all’ as far as environmental values are concerned. Participants recognised the diverse functions served by ecosystems, and were reluctant to harm them for this reason. Whilst the vast majority of respondent sentiments appeared to be captured by the jobs, income, and species attributes, including such attributes without an ecosystem attribute may result in some degree of omitted variable bias. However, the diverse and heterogeneous nature of these effects did not appear to warrant the inclusion of any more closely defined attributes.

Consistent with the framing approach outlined in section 3, the following framing statement was employed in an attempt to minimise perceptions of implausible attribute combinations that may give rise to use of the causal heuristic:

Each option is described in terms of the four[ or five] implications described in the enclosed pamphlet, and the tree levy described above. Because there are many ways of achieving a given level of tree protection, it is important that you consider carefully the implications of each tree-clearing option, by looking at the numbers in the table. To keep matters simple, we do not describe how each option would work. Some implications which may seem a little odd are in fact quite possible...You will find some questions easier than others.

To maintain comparability across versions, this statement was included in both versions of the questionnaire.

Some of the other issues that arose when focus grouping the draft questionnaires concerned the clarity and presentation of information (including the selection of photographic stimuli), cognitive burden and confusion, and perceived bias of information presented. Ways in which the questionnaire could be modified to address these issues were explored. Particular attention was given to whether individuals

10 Copies of the questionnaires are available on request from the principal author.

11 When asked which attributes they had paid most attention to when answering the draft questionnaire, several respondents nominated the ecosystem health attribute, on the basis that “without healthy healthy ecosystems, we can’t have species and jobs”. Such a result is clearly consistent with use of the causal heuristic. Similar findings have been reported in the context of wetland rehabilitation by Morrison, Bennett and Blamey (1997). In that case, ‘water quality’ acted as a surrogate for all other attributes. Focus group participants felt that ‘without good water, you can’t have anything else’.
interpreted information and questions in the way intended by the researchers.

7 Survey Logistics

The final questionnaires were presented in B5 booklets with colour covers, and colour inserts containing an attribute glossary for use when completing the choice sets. A map on the cover indicated the location of the Desert Uplands in Queensland, and proximity to nearby towns. A graphic artist finalised the presentation of the questionnaire and pamphlet.

An orthogonal experimental design was used to assign attribute levels to options. This ensures that the attributes vary independently of one another such that their effects on respondents’ preferences can be isolated. Fractional factorial designs were used to reduce the number of alternatives to a manageable level. Choice sets were constructed in such a way that orthogonality both between and within alternatives was ensured. A correlation between jobs and inc (refer Table 1) was introduced by creating a composite eight level attribute, the purpose being to reduce implausibility problems identified during the focus groups whilst at the same time increasing the balance between environmental and economic variables. Sixty-four choice sets were allocated to eight blocks of eight choice sets in each of the two versions, producing a total of sixteen versions of the questionnaire. An eight-level, orthogonal blocking variable was included as part of the experimental design, and used to generate the eight different blocks or versions of the questionnaire. The purpose of the blocking factor is to ensure that the eight blocks feature a balanced distribution of levels across all attributes, which ordinarily cannot be achieved using random assignment.

A C Neilsen McNair was contracted to administer the final questionnaire following a census style ‘drop-off and pick-up’ procedure. Thirty nodal points were randomly selected throughout the Brisbane metropolitan area. Each of these nodal points was used as a start point for the random selection of 16 respondent households. The final data set contained 480 valid responses, of which 240 were responses to the questionnaire containing the ecosystem attribute.

Table 1: Attributes, Levels and Corresponding Variables

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Levels</th>
<th>Variable in Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Levy on income tax</td>
<td>Option A: $0 (base)</td>
<td>levy</td>
</tr>
<tr>
<td></td>
<td>Options B, C: $20, $60, $100, $140</td>
<td></td>
</tr>
<tr>
<td>Income lost to the region ($ million)</td>
<td>Option A: 0</td>
<td>inc</td>
</tr>
<tr>
<td></td>
<td>Options B, C: 5, 10, 15</td>
<td></td>
</tr>
<tr>
<td>Jobs lost in region</td>
<td>Option A: 0</td>
<td>jobs</td>
</tr>
<tr>
<td></td>
<td>Options B, C: 10, 15, 20, 30, 40</td>
<td></td>
</tr>
<tr>
<td>Number of endangered species lost to region</td>
<td>Option A: 18</td>
<td>end</td>
</tr>
<tr>
<td></td>
<td>Option B, C: 4, 8, 12, 16</td>
<td></td>
</tr>
<tr>
<td>Reduction in population size of non-threatened species</td>
<td>Option A: 80%</td>
<td>pop</td>
</tr>
<tr>
<td></td>
<td>Option B, C: 30%, 45%, 60%, 75%</td>
<td></td>
</tr>
<tr>
<td>Loss in area of unique ecosystems</td>
<td>Option A: 40%</td>
<td>ecos</td>
</tr>
<tr>
<td></td>
<td>Option B, C: 15%, 22%, 28%, 35%</td>
<td></td>
</tr>
</tbody>
</table>
Table 2: Non-Attribute Variable Definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>Alternative-specific constant taking on a value of 1 for options 2 and 3 in the choice sets, and 0 for the base option.</td>
</tr>
<tr>
<td>const1</td>
<td>Alternative-specific constant taking on a value of 1 for option 2 in the choice sets, and 0 for the base option.</td>
</tr>
<tr>
<td>envatt</td>
<td>Dummy variable taking on a value of 1 for respondents indicating that, over the years, when have heard about proposed conflicts between development and the environment, they have tended to “More frequently favour preservation of the environment”; 0 otherwise.</td>
</tr>
<tr>
<td>confuse</td>
<td>Five point likert scale response indicating extent of disagreement with the statement “I found questions 3 to 10 [the choice set questions] confusing”.</td>
</tr>
<tr>
<td>object</td>
<td>Five point likert scale response indicating extent of disagreement with the statement “A tree levy is a good idea”.</td>
</tr>
<tr>
<td>version</td>
<td>Dummy variable equalling 1 when the ecosystem attribute is excluded, 0 otherwise.</td>
</tr>
</tbody>
</table>

8 Results

Tables 1 and 2 define the constants and variables included in the choice models presented in this section. Note that in contrast to the variable ‘envatt’, which provides a measure of respondents’ general stances on environmental issues, the ‘confuse’ and ‘protest’ variables relate to respondents’ reactions to the survey instrument. Respondent income was not significant in any of the models and is not considered further.

Initial results employing an MNL model specification were found to suffer from serious violations of the IIA assumption, using the Hausman and McFadden (1984) test. The violation was addressed by using a nested logit model with the two environmental improvement alternatives grouped in one branch and the status-quo or do-nothing option in the other. A branch-choice equation was specified in which respondents are first seen to choose between ‘doing something’ and ‘doing nothing’. The utilities of these two branches
depends on an ASC and its interaction with environmental attitudes, self-reported confusion, and self-reported levy protest. At the second level of the nest, respondents are assumed to choose on the basis of the attributes of the alternatives.

Results are presented in Table 3. At the top level of the nest, all interactions with the ASC have the expected signs and are highly significant. Respondents with a pro-environment orientation are more likely to choose one of the improvement options than those with a pro-development perspective. Those who report being confused are more likely to choose the status quo, as are those who have a problem with the notion of a tree levy. These apparent status-quo biases are consistent with the findings of Adamowicz et al (1988) reported earlier. The results suggest that, despite the best efforts to minimise confusion and protest through the trial of numerous different framing statements and payment vehicles in focus groups, a significant degree of confusion and protest remains. This has a bearing on which option respondents chose.

Hypothesis 1
Before conducting a formal test of the equality of parameter vectors across the two treatments, it is useful first to conduct a visual examination. Figures 2 and 3 plot the parameter vectors shown in Table 3, with the latter more clearly showing the attribute parameters. An examination of Figure 2 suggests quite high proportionality between the two parameter vectors, with the exception of the parameters for const and the interaction of const with confuse. Eyeing in a line of best fit in Figure 3 indicates that the ratio of ‘without ecosystem’ to ‘with ecosystem’ parameters is greater than one, implying lower variance when the ecosystem attribute is present. It may be that the addition of the ecosystem attribute had no systematic influence on the main taste parameters, only affecting results via differences in variance. If inclusion of the causally prior attribute results in greater homogeneity with respect to choice strategies (including heuristics), one would expect variance to decrease.

The grid search technique was applied to the stacked data sets for two different model specifications. Model 1 in Table 4 involves the same specification as the models in Table 3. In this rather ambitious model, all parameters, including the ASC terms, are constrained to be equal across the two treatments, providing an unqualified test of equality in parameter vectors. The maximum log-likelihood for model 1 in Table 4 corresponded to $\lambda_{1|2}^{12} =0.75$. The likelihood ratio test statistic is $LR=-2[-3257.815-(-1685.564 + -1547.388)] = 49.7$. The critical value of the chi-square distribution is 18.3 at the 95% significance level on 10 degrees of freedom. $H_{1b}'$ is thus rejected. Scale differences do not account for all of the differences in the two data sets. This is not surprising, given the above observations regarding Figures 2 and 3.

Model 2 allows all ASC terms to differ between treatments and rescales only the common attribute parameters. The Swait-Louviere test can be used to test whether this reduced set of equality restrictions provides as good a fit as the separate models shown in Table 3. The maximum log-likelihood for model 2 corresponded to $\lambda_{1|2}^{12} =0.78$. The likelihood ratio test statistic is $LR=-2[-3236.586-(-1685.564 + -1547.388)] = 7.32$. The critical value of the chi-square distribution is 11.07 at the 95% significance level on 5 degrees of freedom. The hypothesis that the vector of common attribute parameters is equal across data sets, thus cannot be rejected. To test whether the scale parameters are equal across data sets requires a further likelihood ratio test. Model 2 in Table 4 is re-run with the restriction that $\lambda$ is no longer allowed to differ across data sets. The LR statistic for this test is $LR=-2[-3240.405-(-3236.586)] =7.638$ which exceeds the critical value of 3.84 at the 95% confidence level. Thus, the inclusion of the ecosystem attribute significantly reduces the scale parameter, and hence increases the variance.

Thus, whilst inclusion of the ecosystem attribute does not appear to have had a significant effect on the taste parameters for the other design variables, it has affected the alternative-specific utility component.
Table 3: Nested Logit Results for Separate Data Sets

<table>
<thead>
<tr>
<th>Utility Functions</th>
<th>With ecosystem attribute (data set 1)</th>
<th>Without ecosystem attribute (data set 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coeff.</td>
<td>s. error</td>
</tr>
<tr>
<td>const1</td>
<td>0.1644#</td>
<td>0.0663</td>
</tr>
<tr>
<td>levy</td>
<td>-0.0107*</td>
<td>0.0011</td>
</tr>
<tr>
<td>jobs</td>
<td>-0.0324*</td>
<td>0.0053</td>
</tr>
<tr>
<td>inc</td>
<td>-0.0597*</td>
<td>0.0138</td>
</tr>
<tr>
<td>end</td>
<td>-0.1214*</td>
<td>0.0111</td>
</tr>
<tr>
<td>pop</td>
<td>-0.0180*</td>
<td>0.0029</td>
</tr>
<tr>
<td>ecos</td>
<td>-0.0392*</td>
<td>0.0065</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Branch Choice Equations</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>-1.9738*</td>
<td>0.5913</td>
</tr>
<tr>
<td>envatt</td>
<td>1.1344*</td>
<td>0.1105</td>
</tr>
<tr>
<td>object</td>
<td>-0.5750*</td>
<td>0.0501</td>
</tr>
<tr>
<td>confuse</td>
<td>-0.1550*</td>
<td>0.0477</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Inclusive Value Parameters</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>do something</td>
<td>0.1904#</td>
<td>0.0795</td>
</tr>
<tr>
<td>do nothing</td>
<td>1.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model Statistics</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>n (choice sets)</td>
<td>1826</td>
<td>1840</td>
</tr>
<tr>
<td>Log L</td>
<td>-1685.564</td>
<td>-1547.388</td>
</tr>
<tr>
<td>adj rho-square (%)</td>
<td>20.1</td>
<td>26.7</td>
</tr>
</tbody>
</table>

NB: + denotes significance at the 10 per cent significance level, # denotes significance at the 5 per cent level, * denotes significance at the 1 per cent level.
Table 4: Nested Logit Results for Pooled Data Sets (Optimally Scaled)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Utility Functions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>const</td>
<td>0.1600*</td>
<td>0.0541</td>
<td>0.1725*</td>
<td>0.0660</td>
</tr>
<tr>
<td>const*version</td>
<td></td>
<td></td>
<td>-0.0637</td>
<td>0.0957</td>
</tr>
<tr>
<td>levy</td>
<td>-0.0114*</td>
<td>0.0009</td>
<td>-0.0114*</td>
<td>0.0009</td>
</tr>
<tr>
<td>jobs</td>
<td>-0.0385*</td>
<td>0.0042</td>
<td>-0.0390*</td>
<td>0.0042</td>
</tr>
<tr>
<td>inc</td>
<td>-0.0823*</td>
<td>0.0111</td>
<td>-0.0821*</td>
<td>0.0111</td>
</tr>
<tr>
<td>end</td>
<td>-0.1649*</td>
<td>0.0094</td>
<td>-0.1648*</td>
<td>0.0093</td>
</tr>
<tr>
<td>pop</td>
<td>-0.0241*</td>
<td>0.0024</td>
<td>-0.0240*</td>
<td>0.0024</td>
</tr>
<tr>
<td>ecos</td>
<td>-0.0120*</td>
<td>0.0026</td>
<td>-0.0389*</td>
<td>0.0064</td>
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<td><strong>Branch Choice Equations</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>const</td>
<td>-0.3872</td>
<td>0.4188</td>
<td>-1.9217*</td>
<td>0.4615</td>
</tr>
<tr>
<td>const*version</td>
<td></td>
<td></td>
<td>1.8378*</td>
<td>0.3966</td>
</tr>
<tr>
<td>envatt*const</td>
<td>1.3198*</td>
<td>0.0916</td>
<td>1.1375*</td>
<td>0.1106</td>
</tr>
<tr>
<td>envatt<em>const</em>version</td>
<td></td>
<td></td>
<td>0.0422*</td>
<td>0.1610</td>
</tr>
<tr>
<td>object*const</td>
<td>-0.7203*</td>
<td>0.0413</td>
<td>-0.5759</td>
<td>0.0502</td>
</tr>
<tr>
<td>object<em>const</em>version</td>
<td></td>
<td></td>
<td>-0.1185</td>
<td>0.0727</td>
</tr>
<tr>
<td>confuse*const</td>
<td>-0.3856*</td>
<td>0.0397</td>
<td>-0.1552</td>
<td>0.0478</td>
</tr>
<tr>
<td>confuse<em>const</em>version</td>
<td></td>
<td></td>
<td>-0.3452</td>
<td>0.0703</td>
</tr>
<tr>
<td><strong>Inclusive Value Parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>do something</td>
<td>0.2646*</td>
<td>0.0569</td>
<td>0.2434</td>
<td>0.0540</td>
</tr>
<tr>
<td>do nothing</td>
<td>1</td>
<td>0</td>
<td>1.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td><strong>Model Statistics</strong></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>optimal scale ratio</td>
<td>0.75</td>
<td></td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>n (choice sets)</td>
<td>3667</td>
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<td>3667</td>
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</tr>
<tr>
<td>Log L</td>
<td>-3257.815</td>
<td></td>
<td>-3236.586</td>
<td></td>
</tr>
<tr>
<td>adj rho-square (%)</td>
<td>22.9</td>
<td></td>
<td>23.3</td>
<td></td>
</tr>
</tbody>
</table>

NB: + denotes significance at the 10 per cent significance level, # denotes significance at the 5 per cent level, * denotes significance at the 1 per cent level.
Figure 2: Parameter Vectors

With Ecosystem Attribute

Without Ecosystem Attribute

Figure 3: Close Up of Attribute Parameter Vectors

With Ecosystem Attribute
Hypothesis 2
Whilst the above results indicate no overall difference in the vector of attribute parameters across treatments, it is conceivable that one or more differences in implicit prices may exist. This question is addressed under H2. The implicit prices for the common non-price attributes are presented in Table 4 for each of the two treatments. Note that the signs of the differences across treatments are as expected a priori in all cases. That is, inclusion of the causally prior ecosystem attribute reduces the importance of the downstream attributes, as reflected by implicit prices. In the case of the endangered species, the difference is statistically significant at p< 0.01. In the case of regional income and population of non-threatened species, the differences are significant at the 10 per cent level but not the 5 per cent level. Thus, whilst no significant differences in the parameter vectors containing the attributes were detected with the Swait-Louviere test, some differences in implicit prices are apparent, and these have the expected sign. Specifically, inclusion of the causally prior ecosystem attribute has reduced the implicit price of endangered species.

Table 4: Implicit Prices

<table>
<thead>
<tr>
<th>Attribute</th>
<th>With Ecosystem</th>
<th>Without Ecosystem</th>
<th>Prob (MRS₁-MRS₂≥ 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jobs</td>
<td>3.04</td>
<td>3.75</td>
<td>0.20</td>
</tr>
<tr>
<td>Inc</td>
<td>5.60</td>
<td>8.63</td>
<td>0.07</td>
</tr>
<tr>
<td>End</td>
<td>11.39</td>
<td>17.17</td>
<td>0.00</td>
</tr>
<tr>
<td>Pop</td>
<td>1.69</td>
<td>2.47</td>
<td>0.08</td>
</tr>
<tr>
<td>Ecos</td>
<td>3.68</td>
<td>n/a</td>
<td></td>
</tr>
</tbody>
</table>

Hypothesis 3
This hypothesis takes on increased importance given the result for H2. The two attribute treatments are compared in terms of the overall welfare estimates generated for two specific scenarios. First, equation (x) is used to estimate compensating surplus associated with a movement from current tree clearing guidelines, with the outcomes listed under Option A in Figure 1, to a new set of guidelines under which less endangered and non-threatened species would be lost (end=16; pop=50). These outcomes correspond approximately to a 30% loss in area of unique ecosystems rather than the 40% that would eventuate under the current guidelines. Associated with the tighter tree clearing guidelines would be additional losses in jobs and regional income (jobs=10; inc=5).

Applying equation (x) to these before and after scenarios produces mean welfare estimates of $76 and $71 respectively for the with and without ecos data sets. These values are calculated at the mean values for protect, confuse and object. Thus, inclusion of the causally prior ecosystem attribute has only slightly increased WTP. A Poe et al test was conducted to determine whether the $76 estimate is significantly higher than the $71 estimate. The difference was not found to be significantly different to zero (p=0.54).12

These welfare estimates represent net improvements in the mean welfare of Brisbane residents resulting from tighter tree clearing guidelines in the Desert Uplands. They are net values in the sense that they reflect losses in use and non-use values associated with the economy of the Desert Uplands region. It is possible to recalculate welfare estimates for the case in which the above environmental improvements are achieved at no cost in the form of lower regional employment and income. When these costs are removed from the environmental improvement scenario, the welfare estimates increase to $87 and $94.

12 Plugging protect=1 (pro-environment orientation) into the model results in respective WTP estimates of $140 and $158 for the two treatments. Plugging protect=0 (pro-development orientation) into the model results in estimates of $33 and $39 respectively. Respondents’ general stances on environmental issues clearly play an important role in how they respond. Some of this effect may involve yea-saying and/or symbolic responses.
respectively. Again, the difference is not statistically significant (p=0.47).

An advantage of incorporating measures of perceived confusion and levy appropriateness within the choice model is that WTP measures can be computed for any level of these variables. For example, if we assign both these variables values of 1.5, corresponding to relatively low levels of confusion and protest, the WTP measures rise substantially. When reductions in employment and income are assumed, as specified above, WTP increases to $175 and $247 respectively. In this case, the hypothesis that the latter is higher than the former is rejected at the 5% significance level, but not the 10% level (p=0.08).

**Hypothesis 4**

Results pertaining to H4a were observed above. Consistent with the occurrence of status-quo bias, those who report being confused are more likely to choose the status quo, in both treatments. Interestingly, an examination of the coefficients for confuse*const*version in model 2 of Table 4 indicates that the negative utility associated with a marginal increase in confusion is greater in magnitude when the ecosystem attribute is excluded.

With regard to H4b, the variable confuse has a mean value of 2.983 when the ecosystem attribute is included and 2.958 when excluded. A paired t-test of the equivalence of these sample means produces a test statistic of 0.23, well below the 95 per cent critical value of approximately 2.0. Thus, confusion levels do not appear to be different across the two treatments.

Overall, the results for H4 are consistent with the findings of Adamowicz et al. Like CVM studies, CM studies are susceptible to status quo biases. Future research might consider how these biases might be reduced in the CM context.

9 Discussion and Conclusion

When selecting attributes in environmental choice modelling studies, preference should be given to those attributes that are demand-relevant, policy-relevant, and measurable. The use of these criteria will often result in a short list of environmental attributes of which some are causally-related. Depending in part on how the CM exercise is framed, the inclusion of causally-related attributes may stimulate some respondents to seek to understand the causal relations among attributes in order to assign greater meaning to the alternatives, and potentially, simplify the decision making process. This potentially has implications for the weights they assign to each of the attributes when identifying their preferred alternatives, and subsequently, implicit prices and/or welfare estimation. Such strategies may not be desirable from a practitioner’s perspective, where respondents are requested to view the attributes as final outcomes. This raises the questions regarding whether causally-related attributes should be included in choice sets, and if so, how they should be presented and explained to respondents.

Limited support was found for the hypothesis that including causally prior attributes such as area of unique ecosystems can affect the importance of downstream attributes. Whilst no significant difference in the attribute taste vectors was detected, the implicit value of a single endangered species fell by 34 per cent when the ecosystem attribute is included. Presumably, this is because part of the utility associated with endangered species is tied up in the ecosystem attribute. Such results, if replicated, would suggest that marginal rates of substitution and hence implicit prices should not be interpreted without an understanding of the role different attributes play when respondents formulate their responses. Like attributes, implicit prices can be causally related and not readily interpreted in isolation to others.

Importantly, however, estimates of compensating surplus did not differ significantly across the two treatments for a given policy package. This implies that to the extent that the inclusion of a causally prior

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13 These latter estimates should only be considered an approximation. Whilst contributions to utility of the job and inc attributes can be controlled for, the ASC terms will to some extent reflect attitudes to employment which cannot be isolated.
ecosystem attribute reduces the implicit prices for one or more of the downstream attributes, the associated loss in utility is approximately offset by the utility now associated with the new attribute. In a sense, the part-worth utilities have been repackaged in such a way that the overall welfare implications of a policy proposal are unchanged. This is an encouraging result as far as the use of CM for welfare estimation is concerned.

The main lesson to be drawn from this study is that care is required to ensure that any causally-related attribute subsets are identified at the preliminary design stage and addressed accordingly. The challenge is to identify the most effective way of administering the questionnaire so as to maximise reliability and validity. The issue arises not simply because of the use of CM, but also because of the nature of the decision problem and the environmental resource together with the level of education, understanding and experience of the sample population. One might expect attributes such as vegetation area, ecosystem damage, and water quality to be particularly prone to causality considerations.

Perhaps the most obvious way of reducing the extent to which respondents consider issues of causality is to exclude causally ‘upstream’ or ‘downstream’ attributes. This may not present a significant omitted variable problem, if the main reason these attributes are valued is their effect (or dependency) on the included attributes. Our findings regarding welfare estimation appear to support this claim. Whether upstream or downstream attributes are omitted will depend in part on which is most relevant to policy. For example, upstream attributes such as ‘area of native vegetation’ will often be more policy-relevant, and measurable, than downstream attributes such as ‘number of non-threatened species lost’. In such cases, it may be preferable to drop the downstream attribute(s). Of course, attributes that are omitted from the choice sets may still need to be described in the preliminary scenario.

Other ways of reducing the extent to which respondents consider issues of causality include giving explanations for the uncorrelated nature of attribute combinations, introducing correlations through the use of composite attributes, and removing the most implausible combinations from the design. An alternative approach is to include the causally prior attributes and to make a more concerted effort to model the resulting effects. For example, it is conceivable that causal effects may involve attribute interactions in addition to the additive effects considered in this study. Special experimental designs are required to permit such interactions to be estimated.

Several further practical issues pertaining to causality arise when selecting from a set of environmental attributes in environmental choice modelling studies. For example, from where in the chain of causes and effects should the attributes be drawn? Does the researcher simply describe native vegetation threatened by clearing, the effects that clearing would have on unique ecosystems, the effect of these ecosystem changes on bird populations and other species, or the effect of protecting bird populations on human health, recreation and other direct human uses? How should a small number of such effects be selected for inclusion in choice sets? And where does the researcher draw the line with respect to how closely attributes must be linked to perceived anthropocentric benefits? When causally-related attributes are included in choice sets, a question arises as to how the associated relations are to be modelled from a production perspective. Whilst complex non-separable production functions can be assumed when predicting the environmental impacts of a policy proposal, these outcomes still need to be mapped into the attribute and label space of the experiment, if welfare estimates are to be obtained.
References


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