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Attribute Causality in Environmental Choice Modelling ⋆

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Abstract. 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. The inclusion of attributes that have a "cause-effect" relationship 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 for the implicit prices and/or welfare estimates. A test of the impact of including an attribute that *causes* impacts on ecosystem health as well as an attribute relating to ecosystem health *effects* on parameter estimates, implicit prices and welfare estimates is conducted. Two questionnaires are developed, one with the 'causal' attribute included and one without. A comparison of results indicates that when the 'causal' attribute is included in the vector of choice attributes, the implicit value of a single endangered species falls by 34 per cent whilst no significant difference is detected in the parameter estimates. Importantly, however, estimates of compensating surplus for a given policy package do *not* differ significantly across the two treatments. This implies that to the extent that the inclusion of a 'causal' attribute reduces the implicit prices for one or more of the 'effect' attributes, the associated loss in utility is approximately offset by the utility now associated with the new attribute.

Key words: attributes, choice modelling, valuation, vegetation

JEL classification: Q20, H41, D61

1. Introduction

The use of Choice Modelling[1] (CM) for the assessment of environmental and recreation values is attracting increasing attention. Examples include: Adamowicz et al. (1998), Boxall et al. (1996), Hanley, Wright and Adamowicz (1998), Bennett

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and Blamey (2001), Morrison and Bennett (2000) and Blamey, Gordon and Chapman (1999).

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 CM studies. For example, the extent to which biases occurring in contingent valuation (CV) studies 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.

One such issue, pertaining to the selection of attributes, is the focus of this paper. When selecting attributes in environmental CM studies, preference should be given to those attributes that are demand-relevant, policy-relevant, and measurable, with the demand component typically being assessed using focus groups. The use of these criteria will often result in a short list of environmental attributes, some of which are causally related. For example, 'causal' attributes pertaining to water quality, the area of vegetation or wilderness, and ecosystem health tend to be short-listed alongside 'effect' attributes such as faunal populations, faunal diversity and/or recreational opportunities. Hence, 'causal' attributes are those that can cause the status or level of expression of another 'effect' attribute. For example, the loss of land classified as wilderness – a 'causal' attribute – may cause losses in an 'effect' attribute such as the size of a population of an endangered species.

In such cases, the CM practitioner has to decide whether to include all of the short-listed attributes, just the 'effect' attributes, or just the 'causal' attribute. Does one include losses in wilderness area and losses in species populations and diversity as attributes in a CM application? Or is it better to include just the species attributes or just the wilderness area attribute? In the event that both causal and effect attributes are included, do respondents treat 'wilderness area' as more fundamental and hence more important than the other environmental attributes? If so, what does this imply for the interpretation of results?

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 them 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. Respondents' adoption of such strategies in formulating their choice responses are not always desirable from a practitioner's perspective, because respondents are expected to assess the alternatives on the basis of the selected attributes as completely representing final outcomes of policy proposals.

The focus of this paper is to examine the implications of including a sub-set of causally-related attributes and to provide a better understanding of the implications of selecting attributes. Whilst the task of selecting attributes is largely dependent on the preferences of respondents, we recognise the importance of attribute selections that are policy relevant and the prospects of respondent driven attribute selection giving rise to inappropriate choice heuristics. Specifically, we test for the effect on parameter and welfare estimates of including a causal attribute within CM choice sets. A briefing on the nature of meaning and causality in the context of CM applications is provided in the next section. Following that, the theoretical specifications Of CM are outlined. The hypotheses established to undertake an examination of the impacts of causally prime attribute inclusion are set out in Section 4. The context in which these hypotheses are tested – the estimation of environmental values associated with remnant vegetation protection in the Desert Uplands region of Queensland Australia – is described in Section 5 and the methods used to test the hypotheses are set out in Section 6. Details regarding the CM application are provided in Sections 7 and 8 whilst results and conclusions are to be found in Sections 9 and 10.

2. 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, individual choice sets, 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.[2] Different categorisations tend to result in different information filtering, organization 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 carrying out focus groups on the 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. Alternatives considered to involve implausible combinations of environmental and/or other attributes may be dismissed, or at a minimum, discounted. Some respondents also seek to assign greater weight to attributes of a more fundamental, causal, nature.

The latter is an example of what psychologists refer to as the causal heuristic, sometimes referred to as the causal schema (Tversky and Kahneman 1982; Einhorn and Hogarth 1985; Heider 1958).[3] As Tversky and Kahneman (1982) 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* (p. 117).

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 ..." (p. 2). Einhorn and Hogarth (1985, p. 313) 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 (usually implicit) of what generates the variable[s]" in question. 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.

Three main ways of reducing the use and/or influence of causal strategies exist. The first involves the inclusion in CM questionnaires of framing statements designed to reduce respondents' use of 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 problematic 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.

The second approach is to introduce correlations to the experimental design that sets up the choice sets. For example, by combining two or more attributes together in a specific way to form a single composite attribute in the experimental design, a correlation can be specifically recognised. Unfortunately, the utility attributable to the sub-attributes often cannot be separated with this approach, since the composite attribute 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 causal or effect attributes from the exercise altogether. Whilst this approach is probably the simplest to implement, the possibility of omitted variable bias remains.

3. Model Specification

Responses to both CM and the dichotomous-choice CV questions can be analysed by invoking assumptions supporting a Random Utility Model (RUM) interpretation of the observed choices. Under this approach, the *i*th respondent is assumed to obtain utility U_{ij} from the *j*th 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 component V_{ij} and a random component u_{ij}. Whilst V_{ij} relates to the measurable component of utility, u_{ij} captures the effect of omitted or unobserved variables. We thus have

$$U_{ij} = V_{ij}(X_{ij}, S_i) + u_{ij}. \tag{1}$$

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

$$\begin{aligned} P_{ih} &= \mathrm{Prob}(U_{ih} > U_{ij}),\ \text{for all } j \text{ in C},\ j \neq h \\ &= \mathrm{Prob}(V_{ih} - V_{ij} > u_{ij} - u_{ih}),\ \text{for all } j \text{ in C},\ j \neq h. \end{aligned} \tag{2}$$

The u_{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 (MNL) model, commonly employed in discrete choice modelling, of which the binary logit used in CV studies is a special case:

$$P_{ih} = \frac{\exp[\lambda V_{ih}]}{\sum_{j \in C} \exp[\lambda V_{ij}]} \tag{3}$$

where λ 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). The estimated utility function for each alternative typically contains the attributes, an alternative-specific constant (ASC), and individual characteristics interacted with the attributes and/or the ASC. The ASC's capture the mean effect of the unobserved factors (u_{ij}) for each alternative.[4]

An alternative to the MNL that allows for correlations among the error terms within different groups or classes of alternatives is the nested logit model[5] (McFadden 1978; Daganzo and Kusnic 1993). In a two level nested logit model, the probability of an individual choosing the hth alternative in class r (P_{hr}) is represented as:

$$P_{hr} = P(h|r)P(r) \tag{4}$$

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

$$P_i(h|r) = \frac{\exp[V_{ihr}/\alpha_r]}{\exp[I_r]} \tag{5}$$

$$\mathrm{P_i(r)} = \frac{\exp[\alpha_r I_r]}{\sum_{k=1}^{R} \exp[\alpha_k I_k]} \tag{6}$$

where

$$\mathrm{I_r} = \log[\sum_{\mathrm{i=1\ to\ Jr}} \exp(\mathrm{V_{ir}}/\alpha_\mathrm{r})] \tag{7}$$

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 α_r measures substitutability across alternatives. When substitutability is greater within rather than between alternatives, $0 < \alpha_\mathrm{r} < 1$. 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 – implicit prices for the individual attributes and compensating surpluses for changes away from the status quo across multiple attributes – are obtained in the MNL case using the formulae described by Hanemann (1984). Kling and Thomson (1996), Herriges and Kling (1997), and Choi and Moon (1997) discuss the required adaptations for the nested logit case. For a two-level nested logit model, the compensating surplus for a change from the status quo with a measurable utility of $\mathrm{Wc(V^0)}$ to a specified alternative providing $\mathrm{Wc(V^f)}$ utility is given by:

$$\mathrm{CS} = \mathrm{Wc(V^0)} - \mathrm{Wc(V^f)} \tag{8}$$

where

$$Wc = \frac{1}{\lambda} \ln \left\{ \sum_{r=1}^{R} \left[\sum_{hr \in Cr} \exp\left(\frac{Vr}{1 - \alpha r} \right) \right]^{(1-\alpha r)} \right\}. \tag{9}$$

4. Hypotheses

The main objective addressed in this paper is to consider the impact of including an environmental attribute that respondents may perceive to have an effect on other included attributes. To achieve this objective, three hypotheses are advanced for testing. The first hypothesis involves a consideration of the impact of including a causal environmental attribute on the overall vector of choice parameters. It is this overall vector that defines the behavioural relationship between the choices respondents make and the independent variables used to explain those choices. The nature of the changes brought about by the inclusion of the causal attribute is not specified:

H1: *Inclusion of a causal attribute changes the behavioural relationship between the dependent variable and the common independent variables.*

The second hypothesis is targeted towards the detection of differences in the marginal rates of substitution (MRS) between attributes brought about because of the inclusion of a causal attribute. Of particular interest are differences in marginal rates of substitution between the environmental attributes and the monetary attribute. These so-called implicit prices are most relevant to welfare estimation. To the extent that inclusion of a causal attribute results in use of a causal heuristic, we would expect respondents to assign lower values to effect attributes. Specifically, H2 is proposed:

H2: *Inclusion of a causal attribute reduces the MRS between the environmental effect attributes and money.*

Rejection of H1 and H2 would imply that the causal heuristic is not the main factor driving a difference in parameter vectors.

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 conceivable that the addition of the causal attribute simply redistributes the source of the utility in terms of the attribute part worths and/or the ASC's. As noted in Section 2, including this attribute may shift respondents' attention from the effect attributes to the causal attributes. The overall utility of a given policy option could thus remain unchanged if a utility decrease with respect to the effect attributes is approximately offset by an increase in the utility derived from the causal attribute. The third hypothesis is thus:

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

The testing of these hypotheses was carried out in the context of a CM study aimed at estimating the environmental costs caused by the clearing of remnant vegetation in the Desert Uplands of Central Queensland, Australia.

5. Case Study

The Desert Uplands is one of thirteen terrestrial biogeographic regions of Queensland, Australia, and consists largely of scattered woodland country. The region is relatively unproductive for pastoral and agricultural purposes compared to other regions in the south and east of Queensland. This is because it has relatively low rainfall, poor soils and vegetation that is relatively unpalatable to domestic stock.

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. 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) and 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 in this paper is directed at estimating.

6. Method

Two questionnaires were designed to examine the impact of the inclusion of a causal attribute and hence to test the three hypotheses set out in Section 4: one in which the choice sets contain the causal attribute, and one in which it is excluded.[6] In all other respects the questionnaires were identical. Each questionnaire was administered to a separate random sample of individuals. Models of the choices made by the respondents to both questionnaire form the basis for the comparative tests called for by the hypotheses.

The procedure outlined by Swait and Louviere (1993) is used to test for parameter vector equality as required under Hypothesis 1.[7] This test is, however, complicated by the presence of a scale parameter (λ) in the estimates of attribute parameter values when derived from a MNL model. The scale parameter is inversely related to the error variance ($\lambda = \pi^2/6\mu^2$). 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. Hence, the Swait-Louviere test must allow for differences in the scale parameter across data sets.

Whilst the Swait-Louviere test 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.

The complications introduced into the testing of Hypothesis 1 by the ASC's and the scale parameters are avoided in the testing of Hypothesis 2. Because the scale factors cancel when dividing attribute parameter coefficients, estimates of marginal rates of substitution between the attributes – in particular the implicit prices – are independent of differences in error variances. Furthermore, there is no requirement to involve the ASC's in these calculations. The convolutions-based method outlined by Poe, Severance-Lossin and Welsh (1994), and Poe, Welsh and Champ (1997) is used to test for significant differences between implicit prices derived from the two alternative models of choice and hence to test the validity of Hypothesis 2.

To test Hypothesis 3, the Poe, Welsh and Champ (1997) procedure is applied to estimates of compensating surplus obtained using the formulae described by Choi and Moon (1997).

Again because the calculation of compensating surplus estimates involves the division of attribute parameter coefficients, the scale parameter issue is avoided. However, this test requires the specification of the levels of the attributes provided under the proposed policy option, including the causal attribute. Hence, the results of the test may be sensitive to the assumed level of the causal attribute. A further caveat is that interactions between the causal and effect attributes are not tested in this paper, as the experimental design employed in this study did not permit these interactions to be properly estimated.

7. Questionnaire Design

The two questionnaires used for the CM application were focused on respondents being asked to choose their preferred option for managing remnant vegetation in the case study region. The key policy deliverable decision parameters for respondents were identified in focus groups sessions. They 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 I were selected. The levels assigned to the attributes were chosen so that the resultant attribute-space would encompass the vast majority of policy-relevant tree clearing options.

Whilst the focus groups indicated that the causal attribute – *loss in area of unique ecosystems* – had importance largely due to its effect on fauna species, its importance was not limited to this role. Ecosystem area appeared to represent somewhat of a 'catch all' as far as environmental values are concerned. Participants recognised the diverse functions served by ecosystems (tourism, agricultural values etc.), and were reluctant to harm them for this reason. 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 2, the following statement was included in both versions of the questionnaire in an attempt to minimise perceptions of implausible attribute combinations that may give rise to use of the causal heuristic:

Table I. Attributes, levels and corresponding variables

Attribute	Levels	Variable in model
Levy on income tax	Option A: $0 (base) Options B, C: $20, $60, $100, $140	levy
Income lost to the region ($ million)	Option A: 0 Options B, C: 5, 10, 15	inc
Jobs lost in region	Option A: 0 Options B, C: 10, 15, 20, 30, 40	jobs
Number of endangered species lost to region	Option A: 18 Option B, C: 4, 8, 12, 16	end
Reduction in population size of non-threatened species	Option A: 80% Option B, C: 30%, 45%, 60%, 75%	pop
Loss in area of unique Ecosystems	Option A: 40% Option B, C: 15%, 22%, 28%, 35%	ecos

> 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 that may seem a little odd are in fact quite possible . . . You will find some questions easier than others.

Each questionnaire contained eight choice sets made up of three alternative vegetation management scenarios. The first of these – Option A – represented the Queensland Government's existing strategy for controlling tree clearing and was held constant across all the choice sets. The other two options – Options B and C – depicted alternative, more restrictive tree clearing guidelines that generated environmental improvements at the cost of a levy on income tax payable. A sample choice set is displayed as Figure 1. The attribute levels used to construct these two options are displayed in Table I. These levels were varied across the options according to an orthogonal experimental design that involved a correlation between *jobs* and *inc* by creating a composite eight level attribute. The use of this composite attribute was designed to reduce implausibility problems identified during the focus groups and to improve the balance between environmental and economic attributes in the choice sets. 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.

Implications	Option A Current guidelines	Option B	Option C
Levy on your income tax	None	$60	$20
Income lost to the region ($million)	None	5	10
Jobs lost in the region	None	15	40
Number of endangered species lost to the region	18	8	4
Reduction in population size of non-threatened species	80%	75%	45%
Loss in area of unique ecosystems	40%	15%	28%

Figure 1. A sample choice set.

8. Survey Logistics

The questionnaires were presented to respondents in 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 'drop-off and pick-up' procedure was used for questionnaire distribution. 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. This corresponds to a response rate of approximately 40 per cent, in which some sample self-selection in favour of higher income, better educated respondents. Of the total number, 240 were responses to the questionnaire containing the causal attribute. Hence the number of choice observations available for modelling is equal to the number of respondents (240 in each sub sample) multiplied by the number of choice sets answered by each respondent (eight) multiplied by the number of options available in each choice set (three).

9. Results

Tables I and II define the ASC's and variables included in the choice models[8] 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.[9] Respondent income, age, sex and educational achievement were not significant in any of the models and are hence not considered further.

Initial results employing an MNL model specification were found to suffer from serious violations of the independence of irrelevant alternatives assumption, using

Table II. Non-attribute variable definitions

Variable	Definition
const	Alternative-specific constant taking on a value of 1 for Options B and C in the choice sets, and 0 for the Option A, base option.
const1	Alternative-specific constant taking on a value of 1 for Option B in the choice sets, and 0 for Option C.
Envatt	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.
Confuse	Five point Likert scale response indicating extent of disagreement with the statement: “I found questions 3 to 10 [the choice set questions] confusing”.
Object	Five point Likert scale response indicating extent of disagreement with the statement: “A tree levy is a good idea”.
Version	Dummy variable equalling 1 when the ecosystem attribute is excluded, 0 otherwise.

Hausman and McFadden (1984) and nested logit tests. 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 (*const*) 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 with the ASC *const1* acting to capture unobserved choice determinants at that level.

Results are presented in Table III. At the top level of the nest, all interactions with the ASC (*const*) have the expected signs and are highly significant. Respondents with a pro-environment orientation are more likely to choose one of the environmental improvement options (Options B and C) than those with a pro-development perspective. Those who report being confused are more likely to choose the status quo (Option A), as are those who protested against the proposed levy on income tax. These apparent status-quo biases are consistent with the findings of Adamowicz et al. (1998). 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. Non-linear (e.g. quadratic) specifications were not found to significantly improve model fit.

Hypothesis 1: The Swait-Louviere grid search technique was applied to the stacked data sets for two different model specifications. Model 1 in Table IV

Table III. Nested logit results for separate data sets

	With ecosystem attribute (data set 1)		Without ecosystem attribute (data set 2)	
	coeff.	s. error	coeff.	s. error
Utility functions				
const1[12]	0.164**	0.066	0.115*	0.069
Levy	–0.011***	0.001	–0.010***	0.001
Jobs	–0.032***	0.005	–0.037***	0.005
Inc	–0.060***	0.014	–0.086***	0.014
End	–0.121***	0.011	–0.170***	0.012
Pop	–0.018***	0.003	–0.025***	0.003
Ecos	–0.039***	0.006	n/a	n/a
Branch choice equations				
Const	–1.974***	0.591	–0.065	0.556
Envatt∗const	1.134***	0.110	1.182***	0.117
Object∗const	–0.575***	0.050	–0.696***	0.053
Confuse∗const	–0.155***	0.048	–0.501***	0.052
Inclusive value parameters				
do something	0.190**	0.079	0.281***	0.073
Model statistics				
n (choice sets)	5769		5784	
Log L	–1685.564		–1547.388	
adj rho-square (%)	20.1		26.7	

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.

involves the same specification as the models in Table III. 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 Swait-Louviere likelihood ratio test statistic is LR = –2[–3257.815 – (–1685.564 + –1547.388)] = 49.7. The critical value of the chi-square distribution is 19.68 at the 95% significance level on 11 degrees of freedom. Scale differences thus do not appear to account for all of the differences in the two data sets.

Model 2 allows all ASC terms to differ between treatments and re-scales 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 III. The likelihood ratio test statistic is LR = 7.32. The critical value of the chi-square distribution is 11.07 at the 95% signi-

Table IV. Nested logit results for pooled data sets (optimally scaled)

	Model 1		Model 2	
	coeff.	s. error	coeff.	s. error
Utility functions				
const1[13]	0.160***	0.054	0.172***	0.066
const1∗version			–0.064	0.096
Levy	–0.011***	0.001	–0.011***	0.001
Jobs	–0.038***	0.004	–0.039***	0.004
Inc	–0.082***	0.011	–0.082***	0.011
End	–0.165***	0.009	–0.165***	0.009
Pop	–0.024***	0.002	–0.024***	0.002
Ecos	–0.012***	0.003	–0.039***	0.006
Branch choice equations				
Const	–0.387	0.42	–1.922***	0.461
const∗version			1.838***	0.397
Envatt∗const	1.320***	0.092	1.137***	0.111
Envatt∗const∗version			0.042***	0.161
Object∗const	–0.720***	0.041	–0.576	0.050
Object∗const∗version			–0.118	0.073
Confuse∗const	–0.386***	0.040	–0.155	0.048
Confuse∗const∗version			–0.345	0.070
Inclusive value parameters				
do something	0.265***	0.057	0.243	0.054
Model statistics				
Optimal scale ratio	0.75		0.78	
n (choice sets)	3851		3851	
Log L	–3257.815		–3236.58	
adj rho-square (%)	22.9		23.3	

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.

ficance 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 IV is re-run with the restriction that λ is no longer allowed to differ across data sets. The likelihood ratio 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 causal attribute significantly reduces the scale parameter, and hence demonstrates an increase in the error variance between the two models.

Table V. Implicit prices

	With ecosystem attribute: Dataset 1 $	Without ecosystem attribute: Dataset 2 $	Prob ($MRS_1 - MRS_2$ >= 0)
Jobs	3.04	3.75	0.20
Inc	5.60	8.63	0.07
End	**11.39**	**17.17**	**0.00**
Pop	1.69	2.47	0.08
Ecos	3.68	n/a	

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.

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 the implicit prices of the attributes may exist. The implicit prices for the common non-price attributes are presented in Table V for each of the two treatments. Note that the signs of the differences between attribute implicit prices across treatments are as expected under Hypothesis 2 in all cases. That is, inclusion of the causal ecosystem attribute reduces the importance of the effect attributes, as reflected by implicit prices. In the case of the 'endangered species' attribute, the difference is statistically significant at $p < 0.01$. In the case of the 'regional income' and 'population of non-threatened species' attributes, 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 causal 'loss of ecosystem area' attribute has reduced the implicit price of the 'endangered species' attribute.

Hypothesis 3: This hypothesis takes on increased importance given the result for Hypothesis 2. The two attribute treatments are compared in terms of the overall welfare estimates generated for two specific scenarios. First, the formula for welfare estimation described by Choi and Moon (1997) was used to estimate compensating surplus. The particular change investigated was associated with a movement from current tree clearing guidelines, with the outcomes listed under Option A in Table I, to a new set of guidelines under which less endangered and non-threatened species would be lost (*end* = 16; *pop* = 50). Associated with the tighter tree clearing guidelines would be additional losses in jobs and regional income (*jobs* = 10; *inc* = 5).

The associated mean welfare estimates are \$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 causal ecosystem attribute has only slightly increased compensating surplus. 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 from zero ($p = 0.54$).[10]

These welfare estimates represent net improvements in the mean welfare of Brisbane residents resulting from tighter tree clearing guidelines in the Desert Uplands. 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 respectively.[11] Again, using a Poe et al. test, 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 compensating surplus estimates associated with changes in attributes away from the status quo can be computed for any level of these variables. For example, if both of these variables are assigned values of 1.5, corresponding to relatively low levels of confusion and protest, the compensating surplus estimates rise substantially. When reductions in employment and income are assumed, as specified above, compensating surplus increases to \$175 and \$247 for the two data sets 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 ($p = 0.08$).

10. Discussion and Conclusion

When selecting attributes in environmental choice experiments, 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.

Limited support was found for the hypothesis that including causal attributes, such as *loss in area of unique ecosystems* can affect the importance of effect attributes. Whilst no significant difference in the attribute taste vectors was detected across the 'with' and 'without' causal attribute data sets, the implicit value of an 'effect' attribute *number of endangered species lost* 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 causal ecosystem attribute reduces the implicit prices for one or more of the effect 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 for practitioners is that of identifying 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, extent of 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 either the causal or the effect 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 causal or effect attributes are omitted will depend in part on which is most relevant to policy. For example, causal attributes such as *loss in area of unique ecosystems* will often be more policy-relevant, and measurable, than effect attributes such as *number of non-threatened species lost*. In such cases, it may be preferable to drop the effect attribute(s). Of course, attributes that are omitted from the choice sets may still need to be described in the preliminary scenario provided to respondents in the questionnaire.

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 experimental design. An alternative approach is to include the causal 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 experiments. 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.

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Notes

1 Otherwise known as Choice Experiments.

2 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, pp. 445–457).

3 A heuristic is a cognitive short-cut that people use to make judgements, often involving uncertain events, and hence probabilities.

4 ASC's are included for all but one of the alternatives presented to respondents in each choice set. Their inclusion 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.

5 Both the MNL and nested logit models rely on an assumption of choice independence. To avoid violations of this assumption, respondents were asked to consider each of their choices as independent events. If respondents failed to take note of this request, it would be necessary to analyse choices using the random parameters logit model as specified by Train (1998) rather than the nested logit model used in this paper.

6 It is implicitly assumed that any differences in the models generated from the data collected from

the two questionnaires are the result of the introduction of a causal attribute. A possible confounding effect on this assumption is that differences result simply from the addition of any attribute. That is, differences are the result of the different number of attributes in the otherwise identical choice sets. The results reported in this paper must be considered in the light of this potentially confounding effect.

[7] The Swait-Louviere test is acknowledged to be relatively inefficient and its use can result in an inappropriate acceptance or rejection of the null hypothesis. To help avoid drawing an incorrect conclusion, the analysis presented here involves testing multiple hypotheses that focus on the one theme.

[8] The choice models were estimated using LIMDEP statistical software.

[9] The use of the covariates *confuse* and *protest* in terms of providing predictions of people's choices in a policy context is limited because information regarding them for the general public is not known. However they are of use in determining the impact on value estimates of features of the questionnaire design. Note also that the respondent reaction variables are self-reported with each respondent determining their own definition of what is confusing or objectionable about the questionnaire.

[10] Substituting *protect* = 1 (pro-environment orientation) into the model results in respective WTP estimates of $140 and $158 for the two treatments. Substituting *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.

[11] These latter estimates should only be considered as approximations. 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.

[12] The significance of *const1* indicates that respondents perceived some systematic difference between the two alternative Options B and C beyond what could be explained by the varying levels of the attributes. For example, respondents may have selected Option B more frequently simply because it was positioned as the middle option in the choice set.

[13] See endnote xii.

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