Testing alternative questionnaire formats for communicating trade-offs in environmental Choice Modelling.

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Testing alternative questionnaire formats for communicating trade-offs in environmental Choice Modelling.[1]

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Abstract

Choice Modelling is a stated preference technique for valuing non-market goods. It has the potential to provide researchers with a rich data set with which to analyse consumer trade-offs between environmental, monetary and social impacts of resource management policies. However, this strength comes at the expense of greater questionnaire complexity relative to other stated preference techniques such as Contingent Valuation. This study examines whether communication aspects of the Choice Modelling questionnaires can be improved through the use of visual stimuli. Split-sample experiments are conducted to test response differences between a 'scaled icons' version of the questionnaire and a conventional 'numbers-only' version. It is found that the different questionnaire versions do not produce significant differences in response rate or preference structures.

Keywords: Choice modelling, non market valuation, environment.

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Introduction

The work reported in this paper is part of a larger study that was commissioned by the National Land and Water Resources Audit to estimate community values for environmental and social attributes in Australia. The overarching goal of the project was to establish a set of attribute values for assessing the non-market cost of land and water degradation at a national level, and for estimating the economic impacts of alternative management strategies. A stated preference survey technique known as Choice Modelling (CM) was used to estimate attribute values.

In a CM questionnaire, respondents are presented with a series of questions, each of which asks respondents to choose their preferred option from several alternatives. The set of options contained in each question is known as choice set. Typically, five to eight choice sets are included in a questionnaire. The options are presented to respondents as the outcomes of different management policies, where the outcomes are described in terms of a standard set of attributes. The options are differentiated from one another by allowing the levels of the attributes to vary systematically according to an orthogonal experimental design. One of the options in each choice set is defined as a 'no change' policy and, as such, the levels of attributes for this option are held constant at the status quo. By including a financial impost as one of the attributes (eg. an environmental levy) it is possible to estimate implicit prices for environmental and social attributes. These 'prices' are a measure of respondents' willingness to trade-off income for environmental and social improvements.

The CM technique produces a rich data set and has some potential advantages over the referendum style Contingent Valuation Method (CVM). However, the questions involved in a CM application are considerably more complex. Work with focus groups has revealed that people find the choice task in a CM questionnaire to be daunting, partly because of the large array of numerical information contained in each choice set (Blamey *et al*., 1997). This could be a significant limiting factor to CM survey response rates. Another concern is that respondents who are confused or over-taxed by the choice task could resort to using heuristics (cognitive shortcuts) without considering the specific levels of the attributes (Blamey *et al*., 1997). An example is the case whereby the respondent makes his or her choice of option on the basis of just one or two attributes, paying no regard to the levels of the other attributes. Evidence of this behaviour would be reflected in the choice data by non-significant coefficients on the ignored attributes. Thus, a high research priority is to develop ways to reduce the cognitive burden of CM questionnaires whilst maintaining a level of choice complexity that reflects the policy issue under investigation.

The study reported in this paper addresses this research objective by devising a questionnaire that uses stylised graphical icons to represent the attributes. The attribute levels are depicted by the size of the icons, which are scaled in approximate proportion to the level. In addition, numerical values for attribute levels are printed below the icons. Split-sample experiments are conducted to test response differences between a 'scaled icons' version of the questionnaire and a conventional 'numbers-only' version. In these experiments, half the sample is administered one version, while the other sub-sample is assigned the other questionnaire version. The data from this experiment is examined to determine whether the icons version;

- increases response rate,
- reduces the level of respondent confusion about the choice task,
- produces a sample of respondents that has an education profile that is more representative of the population (implying a weaker selection pressure for respondents with above-average education),

- increases the statistical significance of attribute coefficients; and
- influences the size of the attribute implicit price estimates.

The paper is organised as follows. The first section contains a brief overview of the statistical and economic theory underpinning the CM technique. In section two, details are provided about the design of each questionnaire version, including a summary of the attributes specified for this application and the scenarios that were presented to respondents. This is followed in section three, by an outline of the sampling strategy and survey logistics. The fourth section contains a description of the model specification. Parameter estimates and results of the split-sample tests are reported in the section five. Conclusions to the study are presented in section six.

1. The Choice Modelling technique

The CM technique originates from the marketing and transport literature where it has been used extensively to analyse consumers' choices of products and transport modes (McFadden, 1974, Ben-Akiva and Lerman, 1985). More recently the technique has been applied to the task of environmental valuation (eg. Adamowicz, Louviere, and Williams, 1994; Bennett and Blamey, 2001; Blamey, Rolfe, Bennett, and Morrison, 2000).

The choices made by respondents to a CM questionnaire are assumed to be a product of utility maximising behaviour. The utility obtained by individual *i* from choosing alternative *j* in a choice set is given by:

$$V_{ij} = (q_j, c_{j,} s_{i,} \varepsilon_{ij}) \qquad 1.$$

where q_j is a vector of outcome attributes, c_j is the cost of the alternative (given by the levy attribute), s_j is a vector of the individual's socioeconomic characteristics, and ε_{ij} is an error term. An error term is included to reflect the fact that the researcher does not know all the factors that contribute to an individual's utility. Thus, the probability of individual *i* choosing alternative *j* is given by:

$$\Pr_{ij} = \Pr[\{v_{ij}(q_j, c_j, s_i) + \varepsilon_{ij}\} \geq \{v_{ik}(q_k, c_k, s_i) + \varepsilon_{ik}\}] \quad \forall j \neq k \qquad 2.$$

This equation says that the probability of a respondent choosing alternative *j* is equal to the probability that the utility associated with that alternative exceeds the utility associated with any other alternative *k* in the choice set. The random utility model is made operational by adopting a particular cumulative density function for the unobserved component of utility, ε. If the ε's are independently and identically distributed with an Extreme Value Type I (Weibull) distribution, then the individual's probability of choosing alternative *j* from a total of *J* possible options is given by a multinomial logit model with the following form (McFadden, 1974):

$$\Pr_j = \frac{\exp(\lambda v_j)}{\sum_{k=1}^{J} \exp(\lambda v_k)} \qquad 3.$$

In this function, V represents the systematic component of utility and λ is a scale parameter[4]. Coefficients of the utility function are estimated by Maximum Likelihood which finds values for the coefficients that maximise the likelihood of the pattern of observed choices. The estimated coefficients are the product of a scale parameter λ and a taste parameter β.

The estimated utility functions permit the calculation of value estimates for environmental and social improvements. Two types of value estimates can be derived from the model. One type of value is the implicit price of a non-market attribute, which is given by the marginal rate of substitution between the non-monetary attribute n and the financial impost. Thus, the implicit price (IP) for an attribute n is calculated as follows:

$$IP_n = \frac{\lambda\beta_n}{-\lambda\beta_\$} \qquad 4.$$

where $\lambda\beta_n$ is the coefficient on the n^{th} environmental or social attribute and $\lambda\beta_\$$ is the coefficient on the monetary attribute. The second type of value estimate provided by the model is a compensating surplus measure of welfare for policies that involve changes in the levels of multiple attributes. The calculation of welfare impacts of this type is beyond the scope of this paper. Instead, the present study focuses on the attribute implicit prices.

2. Questionnaire design

This section describes the methods used to design the questionnaire, with emphasis on the development of the different choice set formats that were adopted for each version of the questionnaire. The first step of the design process was to conduct focus group meetings with members of the public in city and regional areas. An initial round of meetings were conducted to determine the level of public awareness about environmental and social issues associated with land and water degradation, and to identify specific concerns. The concerns expressed by members of the focus groups formed the basis of the attributes selected for the CM application (see van Bueren and Bennett, (2000) for more details).

Five outcome-attributes of land and water degradation were selected. They included three environmental attributes, a 'social impact' attribute and a monetary attribute (Table 1). The environmental attributes were defined so as to capture both the use and non-use values that members of the focus groups appeared to hold for the environment. A social impact attribute was included because the focus group discussions indicated that the public is concerned about rural population decline. It served to capture the effects of resource management policies that either enhance the prosperity of country communities or displace people from rural and regional areas.

The second step of the design process involved the development of a 'prototype' questionnaire consisting of a conventional 'numbers-only' choice set format. In this questionnaire, the choice options were specified in terms of alternative 20 year outcomes which were defined by the attribute levels. Each option included a monetary attribute that was specified as a household levy, levied each year of the 20 year period. For the status quo option, this levy was set to zero. The questionnaire consisted of five choice sets with three alternatives per choice set. The alternatives included a status quo option (A) and two different levy options (B and C). An example of the

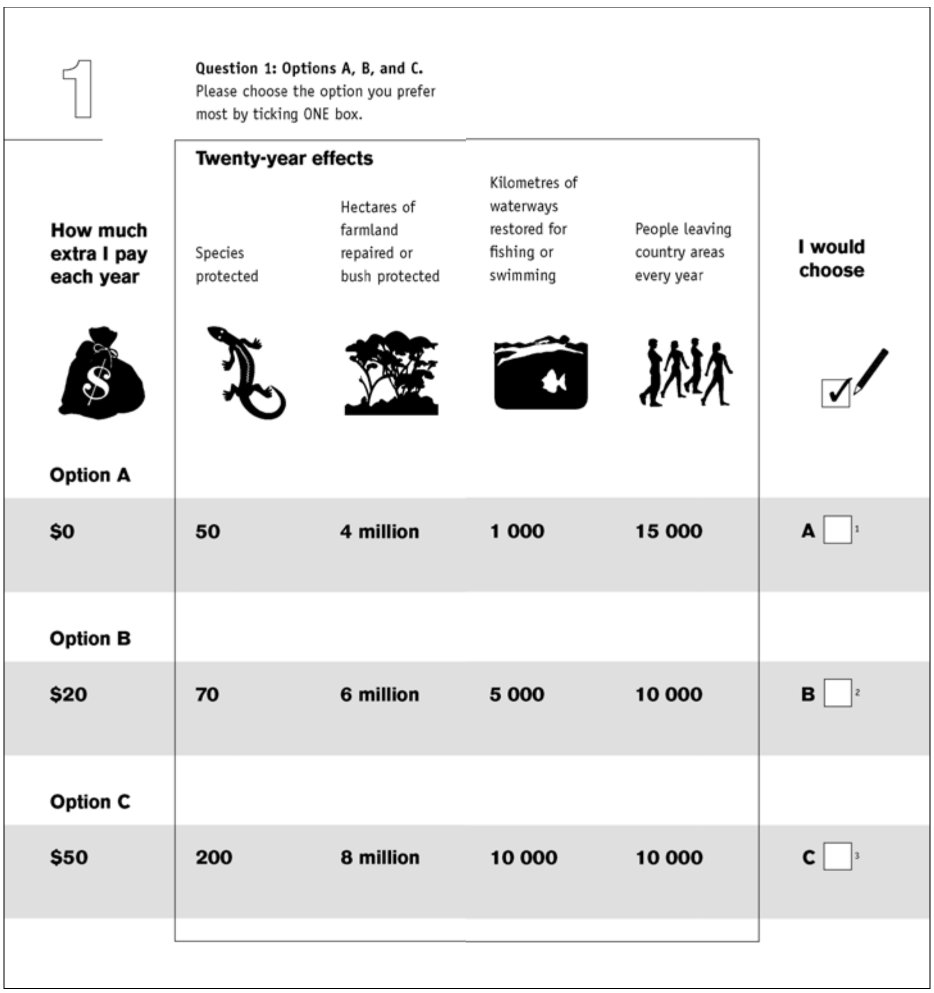
[4] The scale parameter is inversely related to the variance of the error terms and is equal to $\pi^2/6\mu^2$ where μ^2 is the error term variance (Ben- Akiva and Lerman, 1985).

‘numbers-only’ choice set is contained in Figure 1. Note that in this design, icons are used as a means of ‘labelling’ each attribute but they do not indicate their levels.

Table 1 Attributes selected for the choice modelling questionnaire

Attribute	***Unit of measurement***
Endangered native species	The number of species protected from extinction.
Countryside aesthetics	The area of farmland repaired and bush protected (ha).
Waterway health	The length of waterways restored for fishing or swimming (km).
Country communities	The net loss of people from country towns each year.
Environmental levy	Annual household levy ($).

Figure 1: Example of a choice set from the ‘numbers only’ version of the CM questionnaire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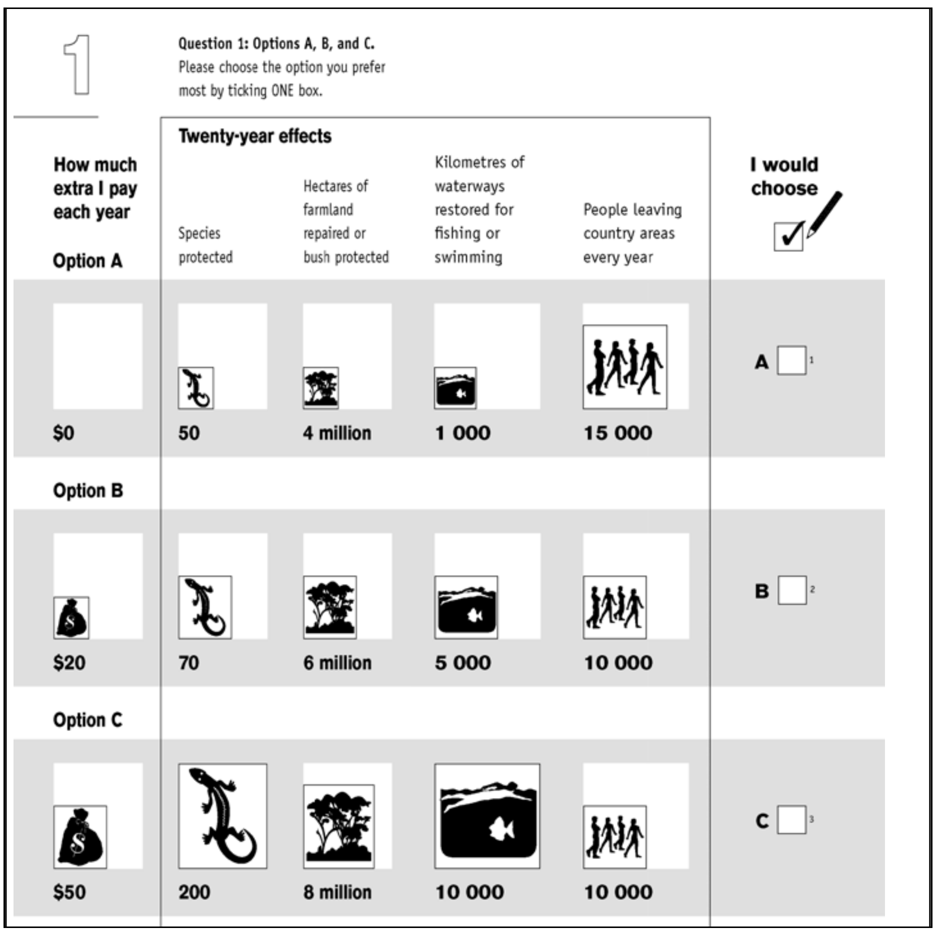
Question 1: Options A, B, and C.
Please choose the option you prefer most by ticking ONE box.

How much extra I pay each year	Twenty-year effects: Species protected	Hectares of farmland repaired or bush protected	Kilometres of waterways restored for fishing or swimming	People leaving country areas every year	I would choose
Option A					
$0	50	4 million	1 000	15 000	A ☐ 1
Option B					
$20	70	6 million	5 000	10 000	B ☐ 2
Option C					
$50	200	8 million	10 000	10 000	C ☐ 3

Three levels were assigned to each attribute, the upper and lower levels being chosen so as to encompass the range of potential outcomes that could eventuate from alternative policies. The levels of the different attributes were combined systematically to make up alternative options according to an experimental design[5]. In order to assist respondents with their deliberations, approximations of the current levels of each attribute were summarised in an introductory pamphlet that accompanied the questionnaire[6].

A second round of focus group discussions was held to 'test' the prototype questionnaire. These discussions revealed that some people were confused by the numbers-only format. Consequently, a variety of different choice sets were developed which used icons to communicate the attribute levels. These alternative formats were presented in focus group meetings and group members were asked to comment on the clarity of each format. A clear preference was expressed for a version that used 'scaled icons' (Figure 2). In this format, the icon boxes are scaled in approximate proportion to the attribute levels.

Figure 2: Example of a choice set from the 'icons plus numbers' version of the CM questionnaire



5 A fractional factorial experimental design was used to assign attribute levels to the alternatives. The resultant alternatives were assigned to 5 blocks such that each respondent was only presented with the alternatives that comprise one block of the fractional factorial.

6 A copy of the complete questionnaire and information pamphlet are available from the authors upon request.

3. Sampling strategy and survey logistics

The two different versions of the CM questionnaire were tested across two separate populations, namely a nationwide sample of households (National) and a regional sample of households from the township of Albany, Western Australia (Regional). The sample frame for each population was the White Pages telephone directory corresponding to each population. The two types of questionnaires were issued to each population by splitting the National and Regional samples into separate sub-samples (Table 2).

Table 2: Sample sizes.

	Questionnaire version		
	Numbers only	**Scaled icons**	***Total***
Population			
National	1600	1600	3200
Regional	600	600	1200

A key hypothesis of this study is that the 'scaled icons' version of the questionnaire would increase response rate. It was further hypothesised that this increase would be strongest amongst respondents with lower levels of education. The sampling strategy facilitates an investigation of this hypothesis because the national population is, on average, more highly educated than the regional population. Persons aged 18 years and over with a tertiary qualification comprise 14% of the national population and 7% of the regional population (Australian Bureau of Statistics, 1996). Therefore, a test of the hypotheses involves a comparison between response rates for the questionnaire versions across the different populations.

The questionnaire was pre-tested over two days using a door-to-door, drop off and pick up method. 25 households were selected for the pre-test. Households from a broad range of socioeconomic strata were included in the pre-test sample. Only minor modifications were made to the questionnaire following the pre-testing phase as debriefs with the respondent households did not reveal any significant communication problems. A market research firm (Barbara Davis and Associates) was contracted to administer the questionnaire as a mail-out; mail-back survey.

4. Model specification

A nested structure was used to model respondents' choices of alternative options[7]. This structure assumes that respondents make an initial upper level decision to either support an environmental levy or retain the status quo (SQ). If the levy was supported, then the respondent was faced with a second-level decision that involved the choice between two different levy options. The utility functions underpinning each choice alternative were specified using the variables described in Table 3.

The utility function associated with the upper-level choice of a levy option was hypothesised to be influenced by the respondent's socioeconomic characteristics (*Age, Sex, Income*), environmental disposition (*Green*), and whether or not the respondent was confused by the background information (*Confuse*). The probability of the levy being supported was expected to increase with income and pro-environment sentiment, but decrease for respondents who reported confusion. In

[7] Initially a multinomial logit model was used to describe the data relationships. However, this specification was shown to result in breaches of the Independence of Irrelevant Alternatives (IIA) assumption. See Kling and Herriges (1995) for more details on nested logit models.

addition to these individual-specific variables, the choice between retaining the status quo or paying a levy was assumed to be influenced by an alternative specific constant (*ASC*) and an inclusive value (*IV*) which is a measure of expected utility from the alternatives nested beneath the upper level choice[8]. The utility functions for the upper level alternatives are given below:

$$V_{levy} = ASC + \beta_1 Sex + \beta_2 Age + \beta_3 Income + \beta_4 Green + \beta_5 Confuse + \alpha_1 \mathrm{IV}_{levy}$$

$$V_{SQ} = \alpha_2 IV_{SQ}$$

At the lower level of the nest, the utility associated with the SQ option and each levy option was assumed to be influenced by the attributes and their corresponding levels. Thus, the utility for option *j* is given by:

$$V_j = \beta_6 Species + \beta_7 Look + \beta_8 Water + \beta_9 Social + \beta_{10} Cost$$

Table 3: Description of explanatory variables

Variable	*Description*
Species	Endangered species, measured by the number of species protected from extinction by 2020.
Look	Landscape aesthetics, measured by the area of farmland repaired and bush protected (hectares) by 2020..
Water	Waterway health, measured by the total length of waterways restored for fishing or swimming (kilometres) by 2020..
Social	Viability of country communities, measured by the net annual loss of population from country towns in 2020.
Cost	The environmental levy, measured as an annual levy on household income over a 20 year time period.
ASC	Alternative specific constant for the levy option, assigned a value of 1 for options B and C and zero otherwise.
Sex	Respondent's gender, assigned a value of 0 for females and 1 for males.
Age	Respondent's age category, ranging from 1 to 6 (youngest to oldest).
Income	Respondent's before-tax household income category, ranging from 1 to 8 (lowest to highest).
Green	Dummy variable assigned a value of 1 for respondents who are members of, or donate to, an environmental organisation and 0 otherwise.
Confuse	Dummy variable assigned a value of 1 for respondents who reported that they found the background information confusing, 0 otherwise.
IV	Inclusive value representing the expected utility from alternatives in the lower level of the nest.

5. Results

Response rates

The total response rate to the CM questionnaire (across all versions and populations) was 17% (Table 4). The type of population did not have an effect on response rate as both the national and regional samples produced a response of 17%. Within each population, the different questionnaire

[8] The IV coefficient for the levy alternative (α_1) is an estimated parameter, while the α_2 coefficient on the status quo IV was restricted to one.

versions appeared to produce some variation in response rate. However, a chi-squared test of the differences indicated that the variations were not statistically significant. Therefore, the hypothesis that the 'scaled icons' version would increase response rates is not supported by the data. A possible explanation for this result is that response rates are being 'held back' by a different constraint. In other words, the choice set format may not be the most limiting factor and there could be other, more serious, obstacles that are preventing people from responding.

Table 4: Survey response rates, by questionnaire version.

	National population			*Regional population*		
	Numbers only	**Scaled icons**	**Combined**	**Numbers only**	**Scaled icons**	**Combined**
Total mailout	1600	1600	3200	600	600	1200
Delivered[A]	1391	1446	2837	558	563	1121
Completed	217	273	490	106	86	192
Response rate[B]	15.6%	18.9%	17.3%	19.0%	15.3%	17.1%

[A] Some questionnaires could not be delivered because contact information was out of date.

[B] Completed as a percentage of delivered.

Respondent selection pressure

Both versions of the CM questionnaire produced respondent samples that contain an above-average proportion of people with tertiary qualifications (relative to the population under investigation). In Table 5 it is shown that for the national sample of respondents, 30 to 40% of people possess a tertiary degree, whilst the national average is 14% (Australian Bureau of Statistics, 1996). Similarly, for the regional sample, 20 to 25% hold a degree but only 7% of Albany people have a tertiary qualification (Australian Bureau of Statistics, 1996).

The hypothesis that the scaled icons version of the questionnaire places less selection pressure on respondents with high education levels is not supported. While the response rates reported in Table 5 do suggest that the icons version produced a more representative respondent sample with respect to education (eg. 39% versus 32% of respondents with a tertiary degree for the numbers and icons versions respectively), chi-squared tests indicate that these differences are not significant.

Table 5: Representativeness of the respondent samples for each questionnaire version, with respect to education.

	National population			*Regional population*		
	Numbers only	**Scaled icons**	**Population**	**Numbers only**	**Scaled icons**	**Population**
Tertiary degree	39%	32%	14%	25%	20%	7%
No tertiary degree	57%	63%	86%	70%	72%	93%
No response	4%	5%	-	5%	8%	-
All respondents	217	273	-	106	86	-

Respondent confusion

A series of debriefing questions were included in both versions of the questionnaire. One of these questions focused on asking respondents about whether they were confused by the options presented to them in the choice sets. The responses to this question are summarised in Table 6. It was expected that the scaled icons version would be less confusing. However, the results do not support this prior. On the contrary, the opposite appears to be the case with a greater proportion of respondents to the icons version reporting confusion than those who answered the numbers only version[9]. However, the between-sample differences in the proportions of people in each response category are not statistically significant.

Table 6: Proportion of respondents reporting confusion about the choice options, by questionnaire version.

	National population		*Regional population*	
Did you find the options confusing?	**Numbers only**	**Scaled icons**	**Numbers only**	**Scaled icons**
Yes	25%	32%	26%	40%
No	44%	42%	48%	36%
Maybe	21%	18%	16%	17%
No response	9%	8%	9%	7%
All respondents	217	273	106	86

Model comparisons and tests

Three models were estimated for each population. The three separate models were estimated using choice data from:

- the sub-sample issued with the 'numbers-only' questionnaire,
- the sub-sample issued with the 'scaled icons' questionnaire,
- a combination of data from both questionnaire versions.

The purpose of this modelling strategy was to determine whether the different questionnaire formats influenced significantly the trade-offs made by respondents and, thus, the estimated taste parameters. Model differences could arise if the icons version was more effective at communicating changes in attribute levels or if it encouraged respondents to consider all the attributes presented rather than just a subset. Another possibility is that the different questionnaire versions could have produced a sample of respondents with different characteristics and tastes.

The maintained hypothesis of parameter equality across the two separate models corresponding to each questionnaire version was tested using a Likelihood Ratio (LR) Test. This test examines whether the separate models for each version are a better description of the choice data than a single model estimated using combined data from both versions. A chi-squared test statistic is given by: $-2[L_c-(L_{icon} + L_{numbers})]$, where L_c is the log likelihood value for the combined model and L_{icon} and $L_{numbers}$ are the log likelihood values for the models estimated using data from the icons and numbers versions of the questionnaire, respectively.

While this test is a useful diagnostic tool for identifying whether coefficients differ significantly across two models, it is not a sufficient basis on which to form a conclusion about the equality of taste parameters. This is because each of the estimated choice model coefficients are the product of a β taste parameter and a λ scale parameter. Thus, if the coefficients are found to differ significantly from one model to the next, either the scale parameter or taste parameter could be responsible for the difference (Swait and Louviere, 1993). One way to isolate the impact of λ from β

[9] A possible explanation for this result is that if respondents to the numbers-only version are, on average, more highly educated than those who responded to the icons survey, then a smaller proportion of respondents might report confusion. However, this reasoning is weak because the results in Table 5 do not support significant differences between the respondent samples with respect to education.

is via the calculation of attribute implicit prices (IP's), as the λ's associated with the monetary and non-monetary attributes in the denominator and numerator, respectively, cancel (Equation 4). Therefore, if attribute implicit prices are found to be statistically equivalent then it can be concluded that the preference structures generated by each questionnaire version are consistent and any observed differences in model coefficients is due to scale parameter differences[10].

National population

Estimation results for the models corresponding to the national population sample are reported in Table 7. Focusing firstly on the combined model, the coefficients for all variables are highly significant and correctly signed. The Log Likelihood Ratio (LRI) of 0.227 indicates that the model has a satisfactory goodness of fit. The other two models in Table 7 correspond to each questionnaire version. While all the attributes are significant in the 'scaled icons' version, the 'numbers-only' questionnaire produces a model in which *Look* and *Water* are not significant. Furthermore, the 'numbers-only' model has a LRI that is lower than that of the 'scaled icons' model, indicating a poorer goodness of fit. These initial observations support the hypothesis that respondents are sensitive to the choice set formats. Further weight is given to this conclusion by the results of a LR test, which rejects the hypothesis of coefficient equality across the two models.

However, upon comparing the attribute IP's derived from each model, it is concluded that the model differences are due to differences in scale parameters rather than unequal taste parameters. This conclusion is reached because the IP estimates calculated using each model for attribute *n* are statistically equivalent, as shown by the overlapping 95% confidence intervals (Figure 3)[11].

Regional population

The conclusion of taste parameter equality between the questionnaire versions is also reached for the regional population sample. Table 8 contains parameter estimates for the models corresponding to each questionnaire version and the combined model. As for the national population sample, a LR test reveals that different questionnaire formats produce statistically different models. And, consistent with the national population, the scale parameter appears to be responsible for the differences because the attribute IP's derived from each of the models are statistically equivalent (Figure 4).

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[10] The Swait and Louviere (1993) test is an alternative method of determining whether taste parameters are equal across models.

[11] Confidence intervals for the implicit price estimates were calculated using the Krinsky and Robb (1986) technique.

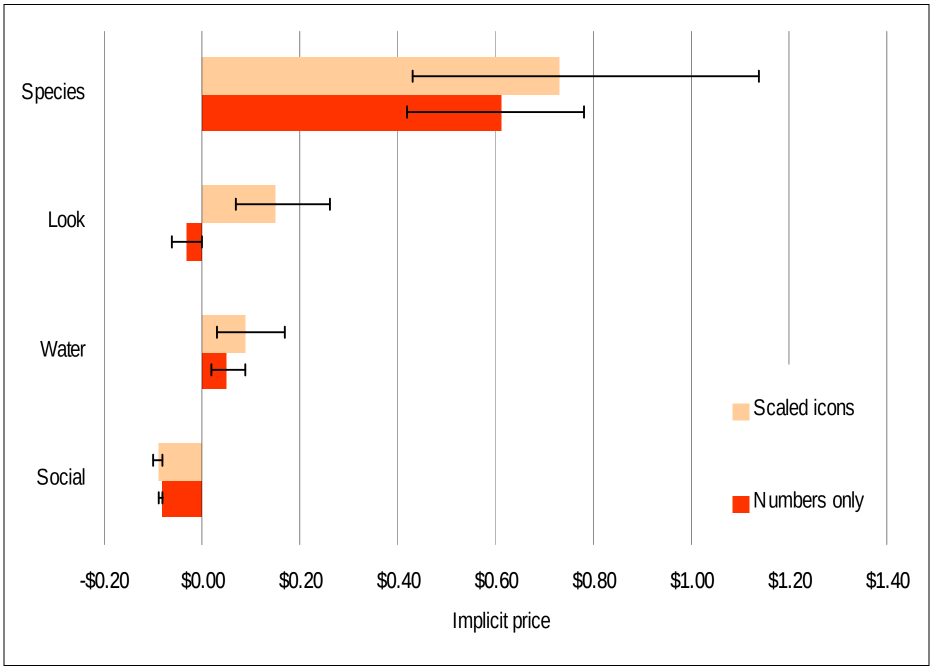
Table 7: Parameter estimates for models based on the national population sample.

	Numbers only	Scaled icons	Combined model
Lower level choice			
Species	4.67E-03 **	6.21E-03 **	5.49E-03 **
Look	-2.38E-08	1.24E-07 **	6.01E-08 **
Water	4.01E-05	7.92E-05 **	6.33E-05 **
Social	-6.41E-05 **	-7.59E-05 **	-6.94E-05 **
Cost	-7.68E-03 **	-8.48E-03 **	-8.13E-03 **
Upper level choice			
ASC	-1.02E+00 **	-2.52E-02	-5.85E-01 **
Sex	-2.47E-01 *	-4.19E-01 **	-3.24E-01 **
Age	9.04E-02	7.19E-02	7.96E-02 **
Income	2.59E-01 **	2.64E-01 **	2.62E-01 **
Green	3.58E-02	8.38E-01 **	2.47E-01 **
Confuse	-5.48E-01 **	-9.14E-01 **	-7.07E-01 **
Inclusive values			
IV staus quo	1.0000	1.0000	1.0000
IV levy	0.4564 **	0.2365 **	0.3434 **
No choice sets	1042	1287	2329
Log Likelihood	-1018.005	-1150.197	-2196.051
LRI	0.17675	0.2832	0.22707
LRI adjusted	0.17199	0.27985	0.22508

* denotes significance of parameter at the 10% level,

** denotes significance at the 5% level.

Figure 3: Attribute implicit prices from the national population sample calculated using data from each questionnaire version. Error bars represent 95% confidence intervals.



Notes: (I) The Look and Water attributes are non-significant in the 'numbers only' version. (ii) Units for the attributes are $ per species protected, $ per 10,000 hectares of land restored (Look), $ per 10 km of waterways rehabilitated, and $ per 10 persons migrating from country towns.

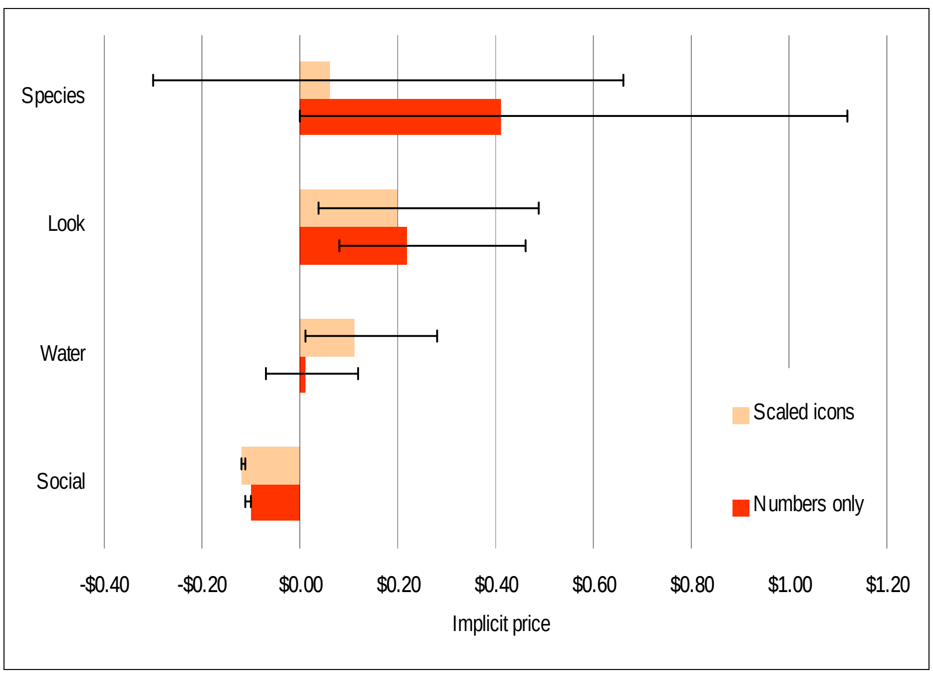
Table 8: Parameter estimates for models based on the regional population sample.

	Numbers only	Scaled icons	Combined model
Lower level choice			
Species	3.18E-03 *	5.92E-04	2.37E-03 **
Look	1.74E-07 **	2.09E-07 **	1.82E-07 **
Water	6.26E-06	1.09E-04 **	4.60E-05
Social	-8.16E-05 **	-1.24E-04 **	-9.50E-05 **
Cost	-7.79E-03 **	-1.04E-02 **	-8.76E-03 **
Upper level choice			
ASC	-1.52E+00 **	-1.05E+00	-1.23E+00 **
Sex	2.10E-01 **	7.05E-01 **	5.18E-01
Age	2.42E-02 *	-2.26E-01 **	-1.10E-01
Income	3.69E-01 **	8.35E-02	2.19E-01 **
Green	9.91E-02 **	7.66E-01 **	4.77E-01
Inclusive values			
IV staus quo	1.0000	1.0000	1.0000
IV levy	0.4991 **	0.2318	0.3679 **
No choice sets	469	391	860
Log Likelihood	-435.9362	-359.4726	-809.8515
LRI	0.24043	0.20214	0.20949
LRI adjusted	0.23142	0.19076	0.20441

* denotes significance of parameter at the 10% level,

** denotes significance at the 5% level.

Figure 4: Attribute implicit prices from the regional population sample calculated using data from each questionnaire version. Error bars represent 95% confidence intervals.



Notes: (I) Species attribute is non-significant in the ‘scaled icons’ version and the Water attribute is non-significant in the ‘numbers only’ version. (ii) Units for the attributes are $ per species protected, $ per 10,000 hectares of land restored (Look), $ per 10 km of waterways rehabilitated, and $ per 10 persons migrating from country towns.

6. Conclusion

The primary objective of this study was to determine whether response rate to a CM survey could be improved, and the representativeness of respondents enhanced, by incorporating visual stimuli into the choice sets. The findings are not encouraging because the 'scaled icons' format employed did not significantly increase response rate. However, the results do not necessarily imply that there is no potential for an icons-style format. It is suspected that another, more limiting factor or factors are responsible for the low response rates. For example, this CM study involved a broad range of environmental goods as it dealt with the general issue of land and water degradation Australia-wide. Had a more specific resource management issue been investigated, with which people can more easily identify, it is possible that the scaled icons would have had a positive influence on response rate. Indeed, a recent application of CM to wetlands by Whitten and Bennett (2001) used visual stimuli in the choice sets and achieved a response rate in excess of 30%. The preliminary findings of the Whitten-Bennett study suggest that graphics should be used more widely in CM applications and that split-sample tests, such as those conducted in this study, be repeated elsewhere.

References

Adamowicz, W., Louviere, J., and Williams, M., (1994), 'Combining revealed and stated preference methods for valuing environmental amenities', *Journal of Environmental Economics and Management* 26: pp. 271-292.

Australian Bureau of Statistics, (1996), *Census of Population and Housing, 1996.* in; 'Community Profiles', www.abs.gov.au.

Ben-Akiva, M. and Lerman, S. R., (1985), *Discrete Choice Analysis: Theory and Application to Travel Demand.* Cambridge, MIT Press.

Bennett, J. and Blamey, R., (2001), *The CM Approach to Environmental Valuation*, Edward Elgar Publishing, Cheltenham, UK.

Blamey, R., Rolfe, J., Bennett, J., and Morrison, M. (2000), 'Valuing remnant vegetation in Central Queensland using choice modelling', *Australian Journal of Agricultural and Resource Economics,* 44:3 pp. 439-456.

Blamey, R.K., Rolfe, J.C., Bennett, J.W., and Morrison, M.D., (1997), Environmental choice modelling: issues and qualitative insights. Research Report No. 4, University College, University of New South Wales, Canberra.

Krinsky, I and Robb, A. L., (1986), 'On approximating the statistical properties of elasticities'. *Review of Economics and Statistics*, 72: pp. 189-190.

McFadden, D. (1974), 'The measurement of urban travel demand', *Journal of Public Economics* 3: pp. 303-328.

van Bueren, M. and Bennett, J., (2000), *Estimating Community Values for Land and Water Degradation Impacts*. A report prepared for the National Land and Water Resources Audit Project 6.1.4 'The non-market costs of land and water degradation in Australia'. Unisearch Pty Ltd., Canberra.

Whitten, S. and Bennett, J., (2001), *Valuing alternative wetland management strategies using Choice Modelling*. Paper presented at the Australian Agricultural and Resource Economics Society Annual Conference, Adelaide, January 22nd to 25th, 2001.