The Australian Journal of
Agricultural and Resource Economics

Journal of the Australian Agricultural and Resource Economics Society

The Australian Journal of Agricultural and Resource Economics, 55, pp. 159–179

Using choice experiments to value catchment and estuary health in Tasmania with individual preference heterogeneity*

Marit E. Kragt and J.W. Bennett†

Choice experiments (CE) have become widespread as an approach to environmental valuation in both Australia and overseas. However, there are few valuation studies that have addressed natural resource management (NRM) changes in Tasmania. Furthermore, few studies have focussed on the estimation of estuary values. The CE study described in this paper aims to analyse community preferences for NRM options in the George catchment, Tasmania. Catchment health attributes were: the length of native riverside vegetation; the number of rare native animal and plant species in the George catchment; and area of healthy seagrass beds in the Georges Bay, which was used as a measure of estuary condition. Mixed logit models with interactions between socio-economic variables and the choice attributes were estimated to account for systematic and random taste heterogeneity across respondents. Results reveal considerable variation in preferences towards the attributes and show that value estimates are significantly impacted by the way in which we account for preference heterogeneity. Preference heterogeneity thus needs to be considered when estimating community willingness-to-pay for environmental changes. This study further shows little responsiveness to the presented changes in estuary seagrass area.

Key words: catchment management, choice experiments, environmental value, interaction effects, mixed logit model, non-market valuation, preference heterogeneity, Tasmania.

1. Introduction

Natural resources in many Australian catchments are under increasing pressure to satisfy often conflicting environmental and economic goals. Increased agricultural run-off, the introduction of exotic species, point source pollution and habitat destruction have led to concerns over catchment ecosystem conditions and water quality in rivers and estuaries. Changes in catchment environments can have significant economic and social impacts on catchment communities. There is an increasing requirement for natural resource

* This research is supported by the Environmental Economics Research Hub and Landscape Logic, both of which are funded through the Commonwealth Environmental Research Facility of the Australian Department of Environment, Water Heritage and the Arts.

† Marit E. Kragt (email: marit.kragt@uwa.edu.au) is Assistant Professor at the School of Agricultural and Resource Economics, The University of Western Australia, Perth, Australia. Jeff W. Bennett is Professor at the Crawford School of Economic and Government, The Australian National University, Canberra, Australia.

doi: 10.1111/j.1467-8489.2011.00533.x

managers to incorporate environmental and socio-economic trade-offs in their decision-making processes. To enable an assessment of the various impacts of catchment management, decision makers need both scientific data on environmental changes and information about the economic values of changes in catchment environment goods and services.

Choice experiments (CE), otherwise known as choice modelling, are a stated-preference approach that is widely used to estimate the value impacts of environmental changes (Alpízar *et al.* 2001; Bennett and Blamey 2001). In a CE, individuals are given a series of questions (choice sets), in which the outcomes of alternative (hypothetical) policy scenarios are displayed. The outcomes of each scenario are described by different characteristics, or levels of attributes. Respondents are asked to choose their preferred option from the array of alternatives. In choosing between alternatives, respondents are expected to make trade-offs between the levels of the attributes. This allows the researcher to observe the relative importance of the different attributes. Where a monetary attribute (cost to the respondent) is included in the choice set, the researcher is able to calculate the average individual's marginal willingness-to-pay (WTP) or 'implicit price' for a change in each of the other (non-marketed) attributes by dividing the estimated coefficient for the non-marketed attribute by the estimated coefficient for the cost attribute (Bennett and Blamey 2001).

Choice experiments studies have been undertaken in various Australian catchments to assess the trade-offs between natural resource management, and environmental and social impacts. Van Bueren and Bennett (2000) used 'waterway health' as one of the attributes in a CE aimed at estimating non-market values associated with land and water degradation in Australia. Waterway health was measured as the total length of waterways suitable for fishing and swimming. Results from nested logit (NL) models indicated that respondents were, on average, WTP \$0.08 per household per year for the next 20 years for waterway restoration. Morrison and Bennett (2004) estimated the benefits of catchment health improvements for five New South Wales River catchments using conditional logit (CL) and NL models. Implicit prices varied across subsamples and ranged between \$1.46 and \$2.33 for a one per cent increase in healthy vegetation along the river; between \$2.12 and \$7.23 for a one species increase in native fish populations; and between \$0.88 and \$1.92 for a one species increase in native waterbirds and fauna populations. A similar application is reported in Bennett *et al.* (2008) for three Victorian rivers. Implicit price estimates from NL models showed that respondents were WTP between \$2.91 and \$5.56 per per cent increase in healthy riverside vegetation; between \$2.19 and \$5.56 per fish species; and between \$3.04 and \$22.07 per species increase in native waterbirds and other animals.

Most published catchment valuation studies focus on attributes that capture river health. There is limited information on estuary values in catchment environments. To the authors' best of knowledge, only two CE studies have estimated estuary values.[1] A study by Johnston *et al*. (2002) considered changes in the Peconic Estuary system in the USA. The authors use four valuation techniques to analyse multiple resource values of the Peconic Estuary system. A hedonic pricing study was used to assess how property values are impacted by nearby open space, farmlands and highways. A travel cost survey was employed to estimate values for outdoor recreational activities. A productivity study yielded estimates of wetland ecosystem values for the production of fish, shell fish and birds. Non-use values were estimated using a contingent choice survey. Results indicated that respondents hold positive values for farmland, eelgrass area, wetlands, shell fishing areas and undeveloped lands in the catchment. However, it can be argued that these estimates include some use value component (such as for the production of shellfish).

An Australian CE application by Windle and Rolfe (2004) aimed to assess community preferences for the protection of the Fitzroy River catchment, in central Queensland. This study included an estuary attribute, described as the 'percentage of the river estuary in good condition'. CL model results indicated that respondents were WTP between $0.50 and $3.89 for a one per cent increase in healthy estuary area.

The studies described above employed either CL or NL models to analyse choice data. In these model specifications, it is assumed that preference structures are homogeneous across respondents (Hanley *et al*. 2006). However, developments in the CE literature have shown the existence of preference heterogeneity that cannot be explained by socio-economic variables (see, for example, Scarpa and DelGiudice 2004) and that not accounting for such unobserved preference heterogeneity can lead to erroneous welfare estimates (see, for example, Rigby and Burton 2005; Espino *et al*. 2008). In this paper, mixed logit (ML) models with interaction terms are used to incorporate preference heterogeneity.

None of the existing Australian valuation studies address catchment management changes in Tasmania. The State of Tasmania also suffers from natural resource degradation, and the Tasmanian Government has acknowledged the possible trade-offs between natural resource protection, and economic and social objectives (DPIW 2005a). In order to support efficient decision making, information is needed about the non-market values associated with protecting Tasmanian catchment environments.

The aim of this paper is to assess community preferences for the protection of rivers and estuary in the George catchment in Tasmania. This paper contributes to the valuation literature by evaluating the impacts on welfare estimates of alternative models specifications that incorporate random and systematic preference heterogeneity. The next section describes

[1] Most CE studies in coastal areas are aimed at estimating values associated with wetlands or marine environments (see EVRI 2009 for more information).

the George catchment case study. In Section three, the development and administration of the CE survey for the George catchment is described. Section four presents the econometric models used in this study. Model results and WTP estimates are presented in Section five. The final section concludes.

2. The George catchment

The study presented in this paper aims to assess the environmental and economic impacts of changed catchment management in the George catchment, in north-east Tasmania (Figure 1). The George catchment is a coastal catchment of about 557 km^2. The total length of rivers in the catchment is approximately 113 km, with the main rivers being the Ransom and the North and South George Rivers. The George River flows into Georges Bay estuary (22 km^2) near the town of St Helens, with a local population of approximately 2200 (ABS 2006). The region is a popular holiday destination, and the rivers in the catchment and the Georges Bay estuary are used for recreational activities such as boating, swimming, sailing and fishing.

Figure 1 Location of the George catchment and sample locations.

Land use in the upper catchment is a mix of native forestry and forest plantations along with dairy farming, while the lower catchment is used for agriculture and contains most of the rural and urban residences (DPIW 2007). Georges Bay has been extensively developed for oyster farming, with most shellfish farming in Georges Bay located within Moulting Bay. Approximately 3000 dozen of oysters were harvested in Georges Bay in 2006 (DEWR 2007).

The catchment environment is generally in good condition (Davies *et al.* 2004; DPIW 2007) but increased clearing of riparian vegetation, stock access to rivers and streams, as well as inputs from forestry operations and other human activities have been identified as threats to catchment water quality and ecosystem health (DPIW 2005b; NRM North 2008). The quality of the George catchment environment is an important issue to local communities (Rattray 2001; Sprod 2003; Break O'Day Council 2007a). Concerns about the George catchment condition vary from protection of river water quality and visual appearance of the river to recreational opportunities and water quality in Georges Bay (Table 1). Management actions aimed at preventing natural resource degradation in the George catchment include fencing to limit stock access to rivers, removing weeds along river banks, developing riparian buffer zones, recovery of dairy effluent and improved wastewater treatment (Lliff 2002; Break O'Day Council 2007b).

Table 1 Significant assets identified in the George catchment (Sources: DPIW 2005b, Rattray 2001; McKenny and Shepherd 1999)

Catchment asset	Specific concerns
Ecosystem protection	1. Maintain existing riparian zones along streams
	2. Maintain good water quality
	3. Improve erosion control (reduced stock access)
	4. Maintain sufficient habitat and flows for rare fish species, birds and Green and Gold tree frogs
	5. Protect seagrass areas in Georges Bay
	6. Protect St Helens Wax Flower
	7. Protect modified ecosystems in Georges Bay from which edible fish, shellfish and crustacea are harvested
Consumptive use	1. Secure adequate water quality for drinking water supply at St Helens
Recreation	1. Protect water quality and quantity for swimming
	2. Maintain and improve angling values
Agricultural water	1. Secure water for irrigational usage and stock watering
	2. Provide a fair system of water allocation
Aesthetics	1. Maintain a good looking river
	2. Maintain reasonable flows over St Columba falls
	3. Maintain and improve riparian zone quality
	4. Reduce weeds and litter along the rivers
	5. Maintain undisturbed status of headwaters

3. Survey development and collection

A CE questionnaire about the management of the George catchment environment was developed in collaboration with local decision makers, natural scientists and community members. The survey design and the data collection are described in this section.

3.1. Survey development

A literature review and interviews with experts on river health, threatened species, riparian vegetation and estuary ecology underpinned the initial selection of the attributes included in the choice sets (Kragt and Bennett 2008). Important attributes were identified and discussed during eight focus group discussions organised in Hobart, Launceston and St Helens in February and August 2008. Draft versions of the questionnaire were also pretesting during these focus groups. The Georges Bay estuary was identified by focus group participants as an important attribute. An explicit estuary attribute was therefore included in the questionnaire. Given that seagrass is often used as an indicator of estuary water quality (see, for example, Crawford 2006; Scanes *et al.* 2007), the area of healthy seagrass beds in the Georges Bay was selected as the estuary condition attribute. Other attributes, identified as important by scientists and focus group participants, were included to characterise the condition of the overall George catchment environment: rare native animal and plant species, and native riverside vegetation. A payment attribute was included in each choice set, defined as a one-off levy on rates, to be paid by all Tasmanian households during the year 2009 (Table 2).

The levels of the attributes included in the choice sets reflected the different situations that could occur in the George catchment under alternative catchment management strategies. The levels of the environmental attributes were identified based on the best available scientific knowledge through a combination of literature review, expert interviews and biophysical model predictions. The cost levels were based on previous CE studies in Australia and on feedback from the focus group participants. The levels of the attributes were defined in a way that was understandable and acceptable to respondents (Kragt and Bennett 2008). Each choice set consisted of a no-cost, no-new-catchment-management base alternative, presented as a likely degradation in catchment conditions over the next 20 years. In this scenario, the environmental attributes would fall to their lowest predicted levels. Two alternative options in each choice set described the implementation of new natural resource management actions and their resulting protection of the environmental attributes (compared to the base alternative). The attributes and the levels of the attributes are presented in Table 2 and an example of a choice set is shown in Appendix II.

Table 2 Attributes, attribute description and levels included in the George catchment choice experiments

Attribute	Description	Levels†
Native riverside vegetation	Native riverside vegetation in healthy condition contributes to the natural appearance of a river. It is mostly native species, not weeds. Riverside vegetation is also important for many native animal and plant species, can reduce the risk of erosion and provides shelter for livestock	40, 56, **74**, 84 (km)
Rare native animal and plant species	Numerous species living in the George catchment rely on good water quality and healthy native vegetation. Several of these species are listed as vulnerable or (critically) endangered. They include the Davies' Wax Flower, Glossy Hovea, Green and Golden Frogs and Freshwater Snails. Current catchment management and deteriorating water quality could mean that some rare native animals and plants would no longer live in the George catchment	35, 50, 65, **80** (number of species present)
Seagrass area	Seagrass generally grows best in clean, clear, sunlit waters. Seagrass provides habitat for many species of fish, such as leatherjacket and pipefish.	420, 560, **690**, 815 (ha)
Your one-off payment	Taking action to change the way the George catchment is managed would involve higher costs. The money to pay for management changes would come from all the people of Tasmania, including your household, as a <u>one-off levy</u> on rates collected by the Tasmanian Government during the year 2009 The size of the levy would depend on which new management actions are used The money from the levy would go into a special trust fund specifically set up to fund management changes in the George catchment An independent auditor would make sure the money was spent properly	**0**, 30, 60 200, 400 ($) or **0**, 50, 100, 300, 600 ($)

†Currently observed attribute levels in the George catchment in bold. ‡One of the split samples in this study included higher payments to test whether choices are impacted by the levels of the cost attribute.
No significant differences were found in preference structures between the 'low-cost' and 'high-cost' split samples (Kragt and Bennett 2009). The present analysis is therefore based on the complete sample to increase the number of observations and sample representativeness.

The final survey material consisted of an introduction letter, a questionnaire booklet and a poster that provided information about the George catchment using maps, photos and charts (Appendix I). Natural resource management in the George catchment, the environmental attributes and attribute levels were also described in the poster. The questionnaire comprised four sections. An introductory section contained questions on visitation and activities in the George catchment. The next section explained the choice task at hand, followed by the choice questions. A third section aimed to elicit respondents' choice strategies and understanding of the survey. The final section consisted of various socio-economic questions.

3.2. Experimental design

The choice sets were created using a *D*-efficient design, aiming to maximise the expected precision of the parameter estimates (Carlsson and Martinsson 2003). A *D*-efficient design minimises the *D*-error, defined as the determinant of the asymptotic variance–covariance matrix of parameter vector β. To calculate the *D*-error, some information is required about the expected values of β. This prior information was elicited from the results of a survey pretested during the August focus groups. A Bayesian efficient design strategy was employed to account for the uncertainty in the prior parameter estimates (Sándor and Wedel 2001).

A total of 20 choice sets were generated and divided into four blocks, so that each respondent was presented with five choice questions.[2] The ex-post performance of the design can be evaluated by comparing the design efficiency using the prior estimates with the design efficiency using the final data (Scarpa and Rose 2008). The statistical measure to compare prior and ex-post design performance is $= D_b$-error $(\beta_{MNL,0})/D_b$-error $(\beta_{MNL,1})$, where $\beta_{MNL,0/1}$ are the estimated multinominal logit model parameters using the focus group data (0) and the final data (1), respectively. In the George catchment survey, the ratio of prior to post *D*-efficiencies is 0.54, indicating a reduction in design efficiency on the final data. This is as expected, because the design was based on a limited number of focus group responses. The interpretation of the final efficiency is difficult without comparative studies that report the ex-post performance of their designs. Future choice experiment studies are urged to report the ratio of the design criteria to enable further comparisons (see also Scarpa and Rose 2008).

[2] The decision to present five choice questions per respondent was based on the number of choice sets used in previous environmental valuation studies. For example, Hanley *et al.* (2006) presented respondents with four choice sets each, while Scarpa *et al.* (2007) and Ladenburg and Olsen (2008) used six choice sets per respondent. Although larger numbers of choice sets per respondent have been used (see, for example, Alvarez-Farizo *et al.* 2007), feedback from focus group respondents indicated that limiting the survey length was likely to increase response rates. To avoid survey 'fatigue', the number of choice questions was limited to five.

3.3. Data collection

In order to achieve a representative sample of Tasmanian households within the practical limits of this study, the survey sample was restricted to the two largest population centres in Tasmania (Hobart and Launceston) and the local community around the town of St Helens. Each location was divided into multiple smaller local sampling units, stratified to cover the complete sample location and a range of community types. A random sample was taken from these areas, using a 'drop off/pick up' method[3] with the assistance of local service clubs. Surveyors received a training session and detailed instructions on the sampling locations and procedures. The questionnaires were collected between November 2008 and March 2009.

A total of 1432 surveys was distributed, of which 933 (65.2 per cent) were returned. Respondents who consistently chose the base alternative because they protested against paying a government levy were not included in the analysis. This resulted in a total of 832 surveys. Because not all respondents answered all the questions, the total number of choice observations available for analysis was 3948.

In Table 3, the descriptive statistics of the sample used in the estimations are presented. A series of χ^2-test were conducted against the Tasmanian population statistics (ABS 2007). These showed that, although mean income, education and age in the sample were not significantly different from the State average, the sample distribution of the socio-demographic variables is significantly different from the State average. Care should therefore be taken when interpreting the conclusions of this study as population averages.

From a policy perspective, and for more accurate extrapolation of the survey results to the population, it is useful to assess whether differences exist between preferences of within-catchment and out-of-catchment respondents. The sample data show a limited number of responses from the local George catchment area (109 respondents), with most respondents living in Launceston or Hobart. To account for possible taste differences between local and urban respondents, a dummy variable 'urban' (one for the Launceston and Hobart subsamples) was initially in the analysis. For completeness, the main socio-economic descriptors are reported by location in Figure 2. The proportion of women and respondents' age is significantly lower in the St. Helens subsample than in the urban subsamples.[4] There are also statistically significantly more people who did not understand the information or who were confused by the choice task in the St. Helens subsamples.

Two attitudinal variables were also considered in the questionnaire: respondents' understanding of the survey information and the extent to

[3] This method involved surveyors visiting randomly selected households within each stratified sampling unit with the request for survey participation. If a householder agreed to participate, a copy of the questionnaire was left behind and arrangements were made to pick up the completed survey booklet at a convenient time.

[4] P-values of 0.021 and 0.099 compared to the urban samples, respectively.

Table 3 Descriptive statistics of George catchment survey sample†

Variable		Mean	Std	Median	Min	Max
Visitation	Number of visits to the George catchment in the past 5 years	5.32	7.96	2.5	0	25
Age	Respondent age (years)	45.93	14.89	45	18	91
Income	Annual household income ('000 $, before taxes)	73.60	43.73	67.6	7.5	210
Male	= 1 if the respondent is male	0.40	0.49	0	0	1
Education	Respondent education (years)	13.35	2.23	13	8	18
Uni	= 1 if the respondent has at least one year of university training	0.38	0.49	0	0	1
Urban	= 1 if the respondent is from Launceston or Hobart	0.87	0.34	1	0	1
Envorg	= 1 if the respondent is a member of some environmental organisation	0.09	0.28	0	0	1
Underst‡	Understood the information	3.88	0.81	4	1	5
Confuse§	Confused by the choice task	2.86	1.04	3	1	5

†Based on available observations.
‡Measured on a 5-point Likert scale where 1 = strongly disagree and 5 = strongly agree.
§Measured on a 5-point Likert scale where 1 = not at all confused and 5 = very confused.

which respondents found answering the choice questions confusing. These variables were measured on a 5-point Likert scale where 1 = did not understand/was not at all confused, and 5 = fully understood/very confused. Of the 804 respondents who answered the attitudinal questions, the majority (fully) understood the survey information (scores 4 and 5 – 630 respondents), whereas 46 respondents said they did not understand the information. About 29 per cent of respondents were (strongly) confused by the choice task (230 respondents). It was anticipated that respondents' understanding of the information and confusion by the choice task will impact respondents 'certainty' when evaluating the utility of the experimentally designed choice alternatives presented to them. Both variables were therefore included in the model specification as a parameter that affects the scale of the error component associated with these alternatives.[5]

4. Model specifications

Choice experiments have their theoretical foundation in random utility theory and in Lancaster's 'characteristics theory of value' (Lancaster 1966;

[5] We thank an anonymous reviewer for this suggestion.

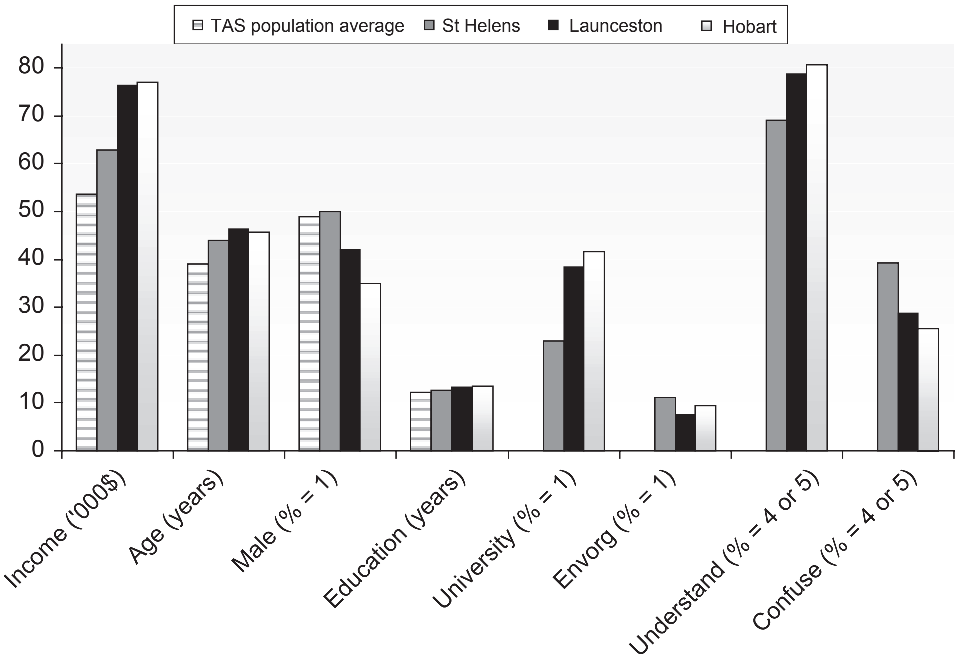


Figure 2 Descriptive statistics by location (measurement units for each variable in brackets).

Louviere *et al.* 2000). The 'workhorse' model to analyse discrete choice data is the CL model (Hensher *et al.* 2005). In the CL model, it is assumed that the error terms are independently and identically distributed (IID) Gumbel distributed over alternatives and individuals. A consequence of this assumption is the independence of irrelevant alternatives (IIA) property, which states that the relative probability of choosing one alternative over another (given that both alternatives have a non-zero probability of choice) is unaffected by the introduction or removal of additional alternatives in the choice set (Louviere *et al.* 2000). Although the IID assumption provides a computationally convenient choice model, it is unlikely to hold if there is unobserved preference heterogeneity among respondents (Louviere *et al.* 2000). In that case, a CL model specification leads to biased parameter estimates.

In this study, ML models were used that relax the IIA assumption. ML models are increasingly used to model (unobserved) preference heterogeneity in discrete choice analysis. The ML model introduces random parameters β_i that vary among the population with density function $f(\beta_i|\theta)$ (Hensher *et al.* 2005). The density function $f(\beta_i|\theta)$ represent the individual preference heterogeneity in the sampled population, with θ a vector of parameters characterising the density function that captures individual deviations from the mean (Hensher *et al.* 2005). A distributional form for θ needs to be specified by the analyst. Commonly used distributions are normal, lognormal, uniform or triangular (Hensher and Greene 2003; Hensher *et al.* 2005). Normal distributions do not constrain the parameter estimates to a specific sign, which may lead to counter-intuitive results, such as a positive coefficient on the cost attribute. Triangular distributions with the standard deviation constrained to equal the mean or lognormal distributions can be used if the analyst wants to restrict the individual parameter estimates to have the same (positive or negative) sign. A drawback of the lognormal distribution is its infinite tail, which can be problematic for WTP estimations (Hensher *et al.* 2005).

A nice feature of ML models is that they can account for the panel structure of the choice data, by including an individual specific error term that is correlated across the sequence of choices made by individual i. Existing CE studies often fail to exploit fully the panel nature of discrete choice data (Bateman *et al.* 2008). In a panel data model, the conditional probability of observing a sequence of individual choices S_i is the product of the conditional probabilities (Carlsson *et al.* 2003). In a typical CE, this sequence of choices is the number of choice questions answered by each respondent. The unconditional choice probability that alternative j is chosen out of J alternatives in choice set t is the expected value of the logit probability over the parameter values. This is the integral over all possible values of β_i, weighed by their probability density (Hensher *et al.* 2005). This model can account for systematic, but unobserved, correlations in an individuals' utility over repeated choices (Revelt and Train 1998). Because the probability function does not have a closed form solution, the model is estimated using simulated maximum likelihood methods (Train 2003).

The panel specification of the model allows for error correlation between choice observations from a given individual. A ML model can further capture error correlation between the alternatives in a choice set by specifying additional error component terms (Scarpa *et al.* 2005). These appear as $M \leq J$ additional random effects (Greene and Hensher 2007):

$$U_{ijt} = \beta_i' X_{ijt} + \varepsilon_{ijt} + d_{jm} W_{im} \quad m = 1, \ldots, M \leq J \tag{1}$$

where W_{im} are normally distributed latent effects with zero mean, and d_{jm} = 1 if the random error component appears in the utility function for j. This extension of the model captures additional unobserved heterogeneity that is alternative- rather than individual-specific (Greene and Hensher 2007). In the present study, it was expected that respondents regard the base alternative in a systematically different manner from the new-management alternatives. To allow for different patterns of error correlation between the new-management alternatives, a shared error component was included for the two new-management alternatives but not in the utility function for the no-cost base alternative (Scarpa *et al.* 2007). A variable for confusion was included in the error component specification to account for the impacts of respondents' confusion on the variance of the latent error component.

An ML model can thus account for unobserved preference heterogeneity across respondents, but does not explain the sources of heterogeneity (Boxall and Adamowicz 2002). One of the objectives in this study was to investigate differences in respondents' attitudes towards the attributes included in the George catchment CE. One way to reveal systematic preference heterogeneity is to introduce an interaction term between socio-economic variables and the choice attributes and/or between socio-economic variables and an alternative specific constant (ASC) in the utility function (Birol *et al*. 2006). In our analysis, we specified an ASC that took a value of one for the two new-management options to test whether respondents had a systematic tendency to prefer the no-cost, no-new-catchment-management base option over the new-management option that could not be explained by observed variables. Socio-economic variables were interacted with the ASC to determine possible sources of heterogeneity in respondents choosing between the no-cost and new-management options. Systematic heterogeneity towards the choice attributes was revealed by interacting each random choice parameter with socio-economic variables (X_i). Thus, the random parameter for the kth attribute faced by individual i is:

$$\beta_{ik} = \beta_k + \delta'_{k\_x} X_i + \sigma_k v_{ik} \quad k = 1, ..., K \text{attributes} \tag{2}$$

where β_k is the unconditional population parameter of the taste distribution; δ_{k_x} are the estimated parameters on the interaction terms; and v_{ik} are the random, unobserved variations in individual preferences that are distributed around the population mean with standard deviation σ_k (Hensher *et al.* 2005).

5. Model results

Nlogit v.4 (Econometric Software 2007) was used to fit CL and ML models, of which the final model specifications are presented in Table 4. Initially, a full set of socio-economic variables was the utility function either through interactions with the ASC or as interaction terms with the choice attributes. Variables such as respondents' household size, gender or association with the farming or forestry community were not significant in the models and are not included in the final model specifications.[6] A Hausman test showed that the IIA property was violated in the CL model, therefore only the ML models are reported in this paper.

5.1. Mixed logit model results

The ML models were estimated by simulated maximum likelihood using Halton draws with 500 replications (Train 2003). All the choice attributes were

[6] Results of these models are available upon request from the authors.

Table 4 Mixed logit model results

Variable	Attribute-only model		Model with interactions	
	Parameter	SE	Parameter	SE
Random parameter means				
Costs ($)	−0.010***	0.000	−0.024***	0.001
Seagrass (ha)	0.001**	0.000	0.001*	0.000
Vegetation (km)	0.040***	0.005	0.070***	0.010
Rare species (#)	0.088***	0.006	0.121***	0.012
Random parameter standard deviations				
Cost	0.010***	0.000	0.024***	0.001
Seagrass	0.004***	0.001	0.006***	0.001
Vegetation	0.050***	0.005	0.030***	0.009
Rare species	0.087***	0.006	0.067***	0.007
Heterogeneity in mean of random parameters				
Cost × Urban			0.013***	0.001
Seagrass × Urban			Fixed	
Vegetation × Urban			−0.039***	0.011
Rare species × Urban			−0.039***	0.012
Non-random parameters				
ASC	2.423***	0.302	2.455***	0.569
Envorg × ASC			3.482**	1.551
Income × ASC			0.010**	0.005
StDev of latent error	7.454***	3.349	5.232***	2.197
Heterogeneity in variance of latent error component				
Understand	−0.518***	0.097	−0.290***	0.081
Confuse	0.353***	0.076	0.298***	0.066
Log-likelihood	−2850.68		−2290.84	
Pseudo-ρ^2	0.3428		0.3734	
Normalised AIC†	1.450		1.386	
Normalised BIC†	1.467		1.416	

Note: ***, **, * significance at 1%, 5% and 10% level. †Normalised to the number of observations in the analysis. ASC, alternative specific constant.

included as random parameters to account for unobserved variation in respondents' preferences. As recommended by Hensher and Greene (2003) and Greene *et al.* (2006), a constrained triangular distribution was used for the random cost parameter to ensure a negative sign on each individual's cost parameter. It was not desirable to so constrain the distributions on the environmental attributes, as respondents may have positive or negative preferences towards the attributes. A normal distribution was therefore defined for the environmental attributes. Other distributional forms or specifying one or more of the environmental attributes as fixed attributes did not lead to significantly better models.

The first model reported in Table 4 includes only the choice attributes as explanatory variables in the utility function. The estimated coefficients all have the expected signs. Cost of new management is negative and significant, whereas an increase in seagrass area, riverside vegetation and rare species are positive and significant at the five per cent level. The standard deviations for the random parameters reveal significant unobserved heterogeneity across individual choices for all attributes. The ASC parameter is positive and significant, indicating that respondents generally prefer the 'new-management' options over the no-management scenario, *ceteris paribus*.

The ML models include an additional latent error term to capture unobserved error correlations between the two new-management alternatives. The error component is significantly different from 0, indicating heterogeneity across the utilities that respondents derive from the new-management alternatives. Understanding of the survey information and respondents' confusion by the choice task were included as explanatory variables in the variance of the error components. Confirming *a priori* expectations, results show that increased understanding of the survey information is associated with a smaller error variance, while more confusion by the choice sets increases the variance of utilities.

The attribute-only model indicates the existence of preference heterogeneity across respondents but does not provide information about the sources of individual heterogeneity. In the second ML model reported in Table 4, socio-economic variables were interacted with the ASC and the choice attributes. Out of a range of model specifications tested, the model that provided the best fit to our data set included membership of an environmental organisation and income, and interaction effects between urban respondents and the choice attributes in the utility function. Comparing the log-likelihoods and the pseudo-ρ^2 goodness-of-fit measures between models, the second ML model that accounts for sources of preference heterogeneity provides a much better model fit than the attribute-only model.

In this second ML model, the seagrass random variable is only significant at the 10 per cent level, although there is considerable heterogeneity in preferences towards seagrass (as indicated by its significant standard deviation). The coefficients for envorg $\times$ ASC and income $\times$ ASC were positive and significant, indicating that higher incomes and membership of an environmental organisation are associated with a higher probability of choice for the new-management alternatives. The urban variable was interacted with the choice attributes to account for heterogeneity around the mean of the random parameters. The interaction between urban and the cost attribute was positive, indicating that an increase in costs produces less disutility to urban respondents compared to respondents from the local catchment area. The interaction term between urban and seagrass area was found to be insignificant, which means that heterogeneity in preferences towards the seagrass attribute could not be explained by the urban variable, and no interaction term between urban and seagrass was therefore included in the final model.[7] Interactions terms between urban and the vegetation and species attributes were negative. Respondents from the local catchment area thus more strongly prefer increasing the length of riverside vegetation and the number of rare species than urban respondents.

[7] Iinteractions between seagrass and other socio-economic variables collected in the survey were also insignificant.

5.2. Willingness-to-pay estimates

Both ML models were used to obtain respondents' marginal WTP to investigate how alternative ways of accounting for preference heterogeneity affect value estimates. The WTP estimates for a change in the George catchment attributes are presented in Table 5. All WTP measures were calculated using parametric bootstrapping techniques with 10 000 replications from the unconditional parameter estimates. The WTP results are based on the random parameter estimates and account for unobserved heterogeneity in preferences by using the estimated standard deviations on the random parameters in the WTP calculations.

The first set of value estimates is based on the attribute-only ML model, which accounts for unobserved, random taste heterogeneity towards the choice attributes. Results show that median WTP is \$0.11 for a hectare increase in seagrass area, \$3.91 for a kilometre increase in native riverside vegetation and \$8.62 for the protection of each rare native animal and plant species, compared to the base level, *ceteris paribus*. Note that incorporating heterogeneity around the mean random parameters generates a distribution of WTP estimates that varies widely (as indicated by the large standard errors associated with the value estimates), because of the high degree of heterogeneity across respondents towards costs, seagrass, riverside vegetation, and species (see Hanley *et al*. 2005, for similar findings).

The second set of value estimates is based on the ML model with interactions, thus considering both random and systematic taste variation across respondents with similar socio-economic characteristics (Espino *et al*. 2008). Specifically, the WTP estimates account for systematic preference heterogeneity towards the choice attributes through the interaction term with the urban variable. We find a notable reduction in sample median WTP figures when interaction terms are included.

The implicit price estimates for the two models (attribute only and with interactions) were compared using the complete combinational convolutions

Table 5 Median marginal willingness-to-pay (WTP) (\$) estimates for environmental attributes

	Seagrass (ha)		Riverside vegetation (km)		Rare species (#)	
	Median	SE	Median	SE	Median	SE
ML model –attributes only						
Sample average	\$0.11	1.08	\$3.91	3.76	\$8.62	5.03
ML model – with interaction effects						
Sample average	\$0.06	6.31	\$2.07	15.7	\$5.26	23.4
Urban	\$0.06	6.77	\$1.94	16.8	\$5.26	25.1
Local	\$0.04	0.67	\$2.98	2.33	\$5.17	3.17
P†	0.40		0.29		0.39	
P‡	0.41		0.36		0.37	

Note: WTP estimates based on the mixed logit (ML) panel model with interaction effects. †Proportion of estimates $WTP_{urban} > WTP_{local}$. ‡Proportion of $WTP_{attribute\_only} > WTP_{with\_interactions}$.

approach proposed by Poe *et al.* (2005). This consists of calculating all the possible differences between WTP estimates for both models (Czajkowski and Hanley 2009).[8] The *P*-values reported in Table 5 are for the null hypothesis that the values are equal between urban and local respondents. As shown in Table 5, the WTP estimates from the ML model with interactions are not significantly lower than the value estimates from the attribute-only model in the presence of random taste heterogeneity.

A second comparison is between the WTP estimates for urban and local respondents. When we add systematic heterogeneity around the mean, the preservation of a negative sign on the cost attribute is no longer guaranteed, resulting in considerable variability in the WTP estimates, particularly for the urban subsample. Using the same convolutions approach as described above, we find no significant differences between urban and local respondents in the WTP estimates for any of the attributes.

6. Discussion and conclusion

The CE reported in this paper is one of the few valuation studies undertaken in Tasmania. It was aimed at eliciting the values that Tasmanian households hold for protecting natural resources in the George catchment. In line with previous studies on mainland Australia (see, for example, Morrison and Bennett 2004; Bennett *et al.* 2008), results from ML models show that Tasmanians hold, in general, positive values for healthy seagrass beds in the Georges Bay; native riverside vegetation along the George catchment rivers; and rare native animal and plants species in the George catchment. A direct comparison between the WTP estimates for attributes or between different studies is not straightforward, as every study is contextual and disparate measurement units are used for the attributes.

A comment is warranted about the utility specification used in the present analysis. The choice attributes are defined as continuous variables, which implicitly assumes that marginal utilities are constant across the range of attribute-level values. This formulation ignores the prospect of diminishing marginal utility over extended ranges of attribute levels.

There is currently limited information on the non-market values that may be impacted by changes in estuary water quality. This study therefore included changes in seagrass area – often used by scientists and policy makers as an indicator of estuary water quality – as an attribute of estuary values. However, the parameter estimates for seagrass were only significant at the 10 per cent level, indicating a limited responsiveness towards the seagrass attribute. In the survey, seagrass was described as an indicator of 'clean, clear, sunlit waters', and its ecological importance as a habitat for fish species was emphasised on the information poster. Nevertheless, feedback from some

[8] The complete combinational convolutions were calculated based on 1000 bootstraps for each WTP distribution, resulting in 1 000 000 possible combinations of WTP estimates.

respondents indicated that seagrass beds can be perceived as a hindrance to recreational activities. This indicates that seagrass may not be an appropriate indicator to measure public preferences for estuary quality and highlights a disparity between scientific and community understanding of the seagrass attribute. Our findings question the usefulness of seagrass as an indicator of estuary values and warrants further discussion on how to describe and measure estuary quality in valuation studies.

This paper further contributes to the valuation literature by analysing the impacts of modelling random and systematic preference heterogeneity on parameter and welfare estimates. Results from ML models revealed considerable unobserved preference heterogeneity among respondents towards the four choice attributes (costs, seagrass, vegetation and rare species), resulting in a large distribution of the welfare estimates. Accounting for systematic preference heterogeneity through interaction terms with socio-economic characteristics in a ML model significantly improved model fit. Although WTP estimates were lower when systematic taste variation was included in this way, differences between models were not statistically significant because of the high degree of variability in respondents' preferences. These results show that, while the Tasmanian community derives a mean benefit from environmental protection in the George catchment, there are considerable differences between the size of value impacts across respondents. This suggests that future valuation studies need to investigate the consequences of (not) including both random and systematic preference heterogeneity in their model specifications.

References

ABS (2006). *Australian Census 2006*. Australian Bureau of Statistics, Canberra.

ABS (2007). *Statistics – Tasmania, 2007*. Australian Bureau of Statistics, Canberra.

Alpízar, F., Carlsson, F. and Martinsson, P. (2001). Using choice experiments for non-market valuation, *Economic Issues* 8, 83–110.

Alvarez-Farizo, B., Hanley, N., Barberan, R. and Lazaro, A. (2007). Choice modeling at the "market stall": Individual versus collective interest in environmental valuation, *Ecological Economics* 60, 743–751.

Bateman, I.J., Carson, R.T., Day, B., Dupont, D., Louviere, J.J., Morimoto, S., Scarpa, R. and Wang, P. (2008). *Choice Set Awareness and Ordering Effects in Discrete Choice Experiments*, CSERGE Working Paper EDM 08-01. IIED, London, UK.

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

Bennett, J., Dumsday, R., Howell, G., Lloyd, C., Sturgess, N. and van Raalte, L. (2008). The economic value of improved environmental health in Victorian rivers, *Australasian Journal of Environmental Management* 15, 138–148.

Birol, E., Karousakis, K. and Koundouri, P. (2006). Using a choice experiment to account for preference heterogeneity in wetland attributes: The case of Cheimaditida wetland in Greece, *Ecological Economics* 60, 145–156.

Boxall, P.C. and Adamowicz, W.L. (2002). Understanding heterogeneous preferences in random utility models: a latent class approach, *Environmental and Resource Economics* 23, 421–446.

Break O'Day Council (2007a). *Break O'Day NRM Survey 2006 – Summary of Results*. Break O'Day Council, St Helens.

Break O'Day Council (2007b). *Georges Catchment and Estuary Project Overview*. Break O'Day Council, St Helens.

Carlsson, F. and Martinsson, P. (2003). Design techniques for stated preference methods in health economics, *Health Economics* 12, 281–294.

Carlsson, F., Frykblom, P. and Liljenstolpe, C. (2003). Valuing wetland attributes: an application of choice experiments, *Ecological Economics* 47, 95–103.

Crawford, C. (2006). *Indicators for the Condition of Estuaries and Coastal Waters*. Tasmanian Aquaculture & Fisheries Institute, University of Tasmania, Hobart, pp. 39.

Czajkowski, M. and Hanley, N. (2009). Using labels to investigate scope effects in stated preference methods, *Environmental and Resource Economics* 44, 521–535.

Davies, P.E., Long, J., Brown, M., Dunn, H., Heffner, D. and Knight, R. (2004) *The Tasmanian Conservation of Freshwater Ecosystem Values (CFEV) Framework: Developing a Conservation and Management System for Rivers*, Proceedings of the freshwater protected areas conference, 27–28 September 2004, Sydney.

DEWR (2007). *Assessment of the Harvest of Native Oysters (Ostrea angasi) from the Tasmanian Shellfish Fishery*. Department of the Environment and Water Resources, Hobart, pp. 15.

DPIW (2005a). *Water Resources Policy, Generic Principles for Water Management Planning*. Department of Primary Industries, Water and Environment. Water Resources Division, Hobart, pp. 20.

DPIW (2005b). *Environmental Management Goals for Tasmanian Surface Waters. Dorset & Break O'Day municipal areas*. Department of Primary Industries, Water and Environment, Hobart, pp. 38.

DPIW (2007). *Annual Waterways Monitoring Reports 2006: George Catchment*, Department of Primary Industries, Water and Environment, Hobart.

Econometric Software (2007). *NLOGIT 4.0*. Econometric Software Inc., Castle Hill.

Espino, R., Martín, J.C. and Román, C. (2008). Analyzing the effect of preference heterogeneity on willingness to pay for improving service quality in an airline choice context, *Transportation Research Part E: Logistics and Transportation Review* 44, 593–606.

EVRI (2009). Environmental Valuation Reference Inventory. Available from URL: http://www.evri.ca/english/default.htm [accessed 30 July 2009].

Greene, W.H. and Hensher, D.A. (2007). Heteroscedastic control for random coefficients and error components in mixed logit, *Transportation Research Part E: Logistics and Transportation Review* 43, 610–623.

Greene, W.H., Hensher, D.A. and Rose, J. (2006). Accounting for heterogeneity in the variance of unobserved effects in mixed logit models, *Transportation Research Part B: Methodological* 40, 75–92.

Hanley, N., Adamowicz, W. and Wright, R.E. (2005). Price vector effects in choice experiments: an empirical test, *Resource and Energy Economics* 274, 27–234.

Hanley, N., Colombo, S., Tinch, D., Black, A. and Aftab, A. (2006). Estimating the benefits of water quality improvements under the Water Framework Directive: are benefits transferable?, *European Review of Agricultural Economics* 33, 391–413.

Hensher, D.A. and Greene, W.H. (2003). The mixed logit model: the state of practice, *Transportation* 30, 133–176.

Hensher, D.A., Rose, J.M. and Greene, W.H. (2005). *Applied Choice Analysis: A Primer*. Cambridge University Press, Cambridge.

Johnston, R.J., Grigalunas, T.A., Opaluch, J.J., Mazzotta, M. and Diamantedes, J. (2002). Valuing estuarine resource services using economic and ecological models: The Peconic Estuary System study, *Coastal Management* 30, 47–65.

Kragt, M.E. and Bennett, J. (2008). *Developing a Questionnaire for Valuing Changes in Natural Resource Management in the George Catchment, Tasmania*, Environmental Economics

Research Hub Research Report No.8, Crawford School of Economics and Government, Australian National University, Canberra, pp. 64.

Kragt, M.E. and Bennett, J. (2009) *What's Appropriate? Investigating the Effects of Attribute Framing and Changing Cost Levels in Choice Experiments*, 17th Annual conference of the European Association of Environmental and Resource Economists, 24–27 June 2009, Amsterdam, The Netherlands.

Ladenburg, J. and Olsen, S.B. (2008). Gender-specific starting point bias in choice experiments: evidence from an empirical study, *Journal of Environmental Economics and Management* 56, 275–285.

Lancaster, K.J. (1966). A new approach to consumer theory, *Journal of Political Economy* 74, 132–157.

Lliff, G. (2002). *George River Catchment: Plan for Rivercare Works for the Upper Catchment, North George and South George Rivers*. George River Catchment Coordinator, 2002, St Helens.

Louviere, J.J., Hensher, D.A. and Swait, J.D. (2000). *Stated Choice Methods: Analysis and Applications*. Cambridge University Press, Cambridge, UK; New York, NY, USA.

McKenny, C. and Shepherd, C. (1999). *Ecological Flow Requirements for the George River*, Technical Report No. WRA 99/14. Department of Primary Industries, Water and Environment, Hobart, pp. 23.

Morrison, M. and Bennett, J. (2004). Valuing New South Wales rivers for use in benefit transfer, *The Australian Journal of Agricultural and Resource Economics* 48, 591–611.

NRM North (2008). *State of the Region: Water Quality and Stream Condition in Northern Tasmania 2006*. Northern Water Monitoring Team, Launceston.

Poe, G.L., Giraud, K.L. and Loomis, J.B. (2005). Computational Methods for Measuring the Difference of Empirical Distributions, *American Journal of Agricultural Economics* 87, 353–365.

Rattray, T. (2001). *Draft Rivercare Plan 2001 for the Upper George River*. George River Catchment Coordinator, 1998–2001, St Helens.

Revelt, D. and Train, K. (1998). Mixed logit with repeated choices: households' choices of appliance efficiency level, *Review of Economics and Statistics* 80, 647–657.

Rigby, D. and Burton, M. (2005). Preference heterogeneity and GM food in the UK, *European Review of Agricultural Economics* 32, 269–288.

Sándor, Z. and Wedel, M. (2001). Designing conjoint choice experiments using managers' prior beliefs, *Journal of Marketing Research* 38, 430–444.

Scanes, P., Coade, G., Doherty, M. and Hill, R. (2007). Evaluation of the utility of water quality based indicators of estuarine lagoon condition in NSW, Australia, *Estuarine, Coastal and Shelf Science* 74, 306–319.

Scarpa, R. and DelGiudice, T. (2004). Market segmentation via mixed logit: extra-virgin olive oil in urban Italy, *Journal of Agricultural and Food Industrial Organization* 2, 1.

Scarpa, R. and Rose, J.M. (2008). Designs efficiency for nonmarket valuation with choice modelling: how to measure it, what to report and why, *The Australian Journal of Agricultural and Resource Economics* 52, 253–282.

Scarpa, R., Ferrini, S. and Willis, K. (2005). Performance of Error Component Models for Status-Quo Effects in Choice Experiments, in Scarpa, R. and Alberini, A. (eds), *Applications of Simulation Methods in Environmental and Resource Economics*. Springer Publisher, Dordrecht, pp. 247–273.

Scarpa, R., Willis, K.G. and Acutt, M. (2007). Valuing externalities from water supply: status quo, choice complexity and individual random effects in panel kernel logit analysis of choice experiments, *Journal of Environmental Planning and Management* 50, 449–466.

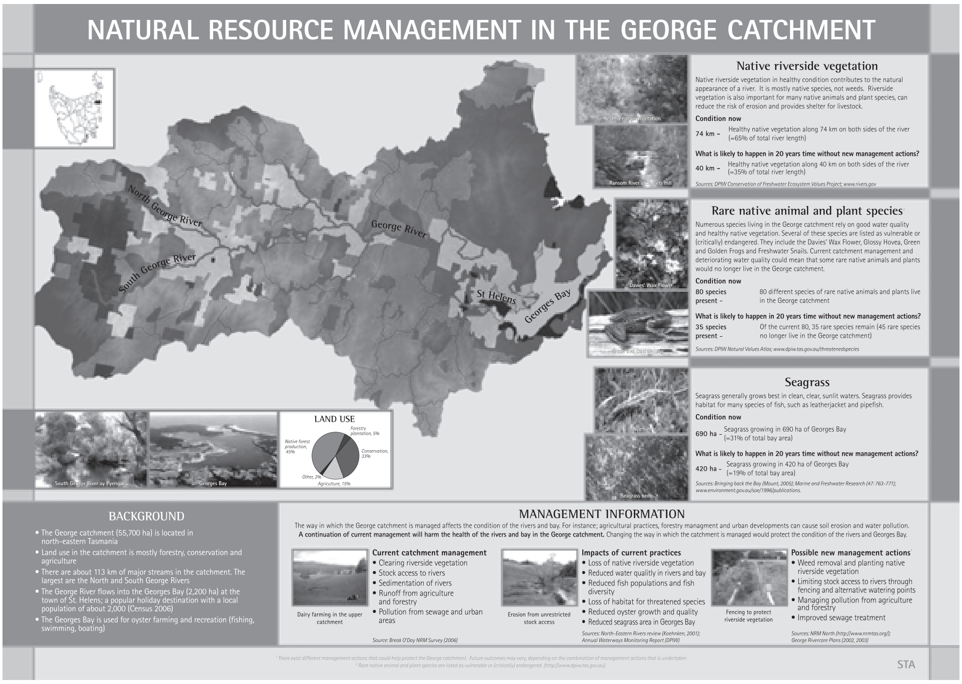
Sprod, D. (2003). *Draft Rivercare Plan Lower George River*. Lower George Landcare Group, St Helens.

Train, K.E. (2003). *Discrete Choice Methods with Simulation*. Cambridge University Press, Cambridge.

Van Bueren, M. and Bennett, J. (2000). *Estimating Community Values for Land and Water Degradation Impacts*, Final Report, Project 6.1.4. National Land and Water Resources Audit, Canberra, pp. 66.

Windle, J. and Rolfe, J. (2004). *Assessing Values for Estuary Protection with Choice Modelling using Different Payment Mechanisms*, Valuing Floodplain Development in the Fitzroy Basin Research Report No.10, Faculty of Business and Law, Central Queensland University, Emerald, QLD, pp. 19.

Appendix I
Information poster included in the George catchment choice experiments



Appendix II
Example choice set

Question 4

Consider each of the following three options for managing the George catchment.
Suppose options A, B and C are the **only ones** available.
Which of these options would you choose?

Features	Your one-off payment	Seagrass area	Native riverside vegetation	Rare native animal and plant species	YOUR CHOICE
Condition now		690 ha (31% of total bay area)	74 km (65% of total river length)	80 rare species live in the George catchment	

Condition in 20 years					Please tick one box
OPTION A	$0	420 ha (19%)	40 km (35%)	35 rare species present (45 no longer live in the catchment)	☐
OPTION B	$60	815 ha (37%)	81 km (70%)	50 rare species present (30 no longer live in the catchment)	☐
OPTION C	$30	690 ha (31%)	74 km (65%)	65 rare species present (15 no longer live in the catchment)	☐