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

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Abstract

Choice experiments (CE – otherwise known as Choice Modelling) have become a widespread approach to environmental valuation in Australia, with many examples assessing the trade-offs between river catchment management and socio-economic impacts. There is, however, limited information on the values of Australian estuaries. Furthermore, none of the existing valuation studies address catchment management changes in Tasmania.

The CE study reported in this paper aims to elicit community preferences for the protection of the rivers and estuary of the George catchment in north-eastern Tasmania. Results from conditional and mixed logit models show that respondents are, on average, willing to pay between \$2.47 and \$4.46 for a km increase in native riverside vegetation and between \$9.35 and \$10.97 per species for the protection of rare native plants and animals, *ceteris paribus*. The results are ambiguous about respondents' preferences for estuary seagrass area. This study further shows significant differences between logit models when accounting for individual heterogeneity and repeated choices made by individual respondents.

Keywords: River condition; Estuary condition; Environmental values; Non-market valuation; Choice Experiments; Tasmania

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1 Introduction

Water resources in Australian catchments are under increasing pressure to satisfy often conflicting environmental and economic goals. Increased agricultural runoff, the introduction of exotic species, point source pollution and habitat destruction have led to concerns over water quality and ecosystem condition in rivers and estuaries. Changes in the catchment environment can have significant economic and social impacts on catchment communities. There is increasing pressure for natural resource managers to incorporate ecological and socio-economic values in decision making processes. However, the information on these different values is limited (Gilmour et al., 2005). To enable an assessment of the various impacts of catchment management, decision makers need scientific data on environmental changes, as well as information on the economic values of catchment environment goods and services.

Choice Experiments (CE), otherwise known as Choice Modelling (CM), have become an increasingly popular stated-preference (SP) approach to valuing environmental changes. CE have been advocated as a flexible and cost-effective technique to estimate the non-market environmental costs and benefits of alternative management strategies (Alpízar et al., 2001, Bennett and Blamey, 2001). In a CE, individuals are given a series of questions (choice sets), where each question shows the outcomes of alternative (hypothetical) policy scenarios. The outcomes are described by different levels of attributes, or characteristics, that depict the good that is being valued. Respondents are asked to choose their preferred option from the array of alternatives. In choosing between alternative options, respondents are expected to make a trade-off between the levels of the attributes. This allows the researcher to observe the relative importance of the different attributes. If 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 or *implicit price* for a change in each of the other (non-marketed) attributes: $WTP_a = - \beta_a / \beta_c$, where WTP_a is the willingness-to-pay for attribute a, β_a is the estimated coefficient for that attribute, and β_c is the estimated coefficient for the cost attribute.

CE studies have been undertaken in various Australian catchments to assess the trade-offs between natural resource management and environmental and social impacts. In a CE study by Morrison and Bennett (2004), the benefits of river health improvements were estimated for five New South Wales Rivers (Bega, Clarence, Murrumbidgee, Gwydir and Georges Rivers). Implicit price estimates from nested logit models showed that respondents were WTP between \$1.46 to \$2.33 for a one percent increase in healthy vegetation, between \$2.12 to \$7.23 for a one species increase in native fish populations and between \$0.88 to \$1.92 for a one species increase in waterbirds and other fauna populations. Another application of CEs in an Australian river health context is described in Bennet et al. (2008). This study was aimed at estimating values for a range of attributes of Victorian rivers (Goulburn, Gellibrand and Moorabool rivers). Environmental attributes included percent of pre-settlement fish species and populations; percent of the river's length with healthy vegetation on both banks; and number of native waterbird and animal species with sustainable populations. Results from nested logit models indicated that respondents were WTP between $2.19 to $22.07 for protecting river health, depending on the environmental attributes being valued. 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 healthy enough for fishing and swimming. Results indicated that respondents were, on average, willing to pay $0.08 per household per year for the next 20 years for waterway restoration. To the authors' best knowledge, only two CE studies have aimed to estimate estuary values[1]. A study by Johnston *et al.* (2002a) considered changes in the Peconic Estuary system in the USA. An Australian CE application by Windle and Rolfe (2004) aimed to assess community preferences for the protection of the Fitzroy River estuary, in central Queensland. The estuary attribute was described as the percentage of the river estuary in good condition. Model results indicated that respondents were WTP between $0.50 and $3.89 for a one percent increase in healthy estuary area.

These previous valuation studies indicate that there are significant community values for protecting river catchments in Australia. However, there is limited information about the values of protecting Australian estuaries. Furthermore, none of the existing valuation studies address catchment management changes in Tasmania.

Tasmania is not immune to water quality deterioration and the Tasmanian Government is committed to protecting the State's water resources, while acknowledging possibly conflicting economic, social and environmental objectives (DPIWE, 2005). In order to balance natural resource protection with the economic impacts of changed catchment management, and to support efficient decision making, information is needed about the non-market values associated with protecting Tasmanian catchment systems.

The study reported in this paper aims to elicit community preferences for the protection of rivers and estuaries for a case study of the George catchment in north-eastern Tasmania. A CE survey has been undertaken in different sub-sample locations in Tasmania to assess the trade-offs respondents may make between river and estuary health. River health attributes included the length of native riverside vegetation and the number of rare species in the George catchment. The area of healthy seagrass beds in the Georges Bay was used as an

[1] CE studies in coastal areas are typically aimed wetland valuation or at estimating values associated with marine environments.

indicator of estuary condition. Model results indicate that Tasmanians hold positive values for the rivers and estuary in the George catchment.

In the next section, the theory of CEs and the econometric models used in this study are explained. Sections three and four describe the case study area and the development of a CE survey for the George catchment. In section five, results of the econometric analyses are presented. The final section concludes.

2 The econometric model

Choice Experiments have their theoretical foundation in random utility theory and in Lancaster's 'characteristics theory of value' (Lancaster, 1966). The random utility model describes utility U_{ijt} that individual *i* derives from choice alternative *j* in choice situation *t* as a latent variable that is observed indirectly through the choices people make. Each utility value consists of an observed 'systematic' utility component V_{ijt} and a random unobserved error term ε_{ijt} (Louviere et al., 2000):

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = \beta_i{}'\mathbf{X}_{ijt} + \varepsilon_{ijt} \qquad j=0,1,...,J;\ t=1,2,...,T \qquad \text{(Equation 1)}$$

The systematic component of utility is assumed to be a linear, additive function of a vector of explanatory variables $\boldsymbol{X}_{ijt}$, which can include the attributes of the alternatives, individual *i*'s socio-economic and behavioural characteristics and features of the choice task itself (Equation 1).

Alternative *j* will be chosen if and only if the utility derived from that option is greater than the utility derived from any other alternative *z* (Equation 2). It is expected that if the quantity or quality of a 'good' attribute in an alternative rises, the probability of choosing that alternative increases, *ceteris paribus*.

$$\Pr(j \mid \mathbf{X}_{ijt}, \varepsilon_{ijt}) = \Pr\{(\beta'_i\, \mathbf{X}_{ijt} + \varepsilon_{ijt}) > (\beta'_i\, \mathbf{X}_{izt} + \varepsilon_{izt})\} \qquad \text{(Equation 2)}$$

Different econometric models can be used to estimate parameter vector β_i. It is often assumed that the error terms are independently and identically distributed (IID) Gumbel distributed over alternatives and individuals. This implies that the individual error terms have the following cumulative distribution function (Swait and Louviere, 1993):

$$F(\varepsilon_{ijt}) = \exp[-\exp(\mu\varepsilon_{ijt})] \qquad \text{(Equation 3)}$$

where μ is a non-negative scale parameter that impacts variance σ_ε^2 of the error distribution through $\mu = \sqrt{(\pi^2/6\sigma_\varepsilon^2)}$ (Cameron and Trivedi, 2005). If it is additionally assumed that β_i does not vary across individuals (that is, $\beta_i = \beta$), the probability that individual *i* chooses alternative

j out of J choice alternatives can be estimated by a *conditional logit* (CL) model[2] specification:

$$\Pr(j|\mathbf{X}_{ijt}, \beta') = \frac{\exp(\mu\beta'\mathbf{X}_{ijt})}{\sum_{j=1}^{J}\exp(\mu\beta'\mathbf{X}_{ijt})} \qquad \text{(Equation 4)}$$

From Equation 4, the estimated parameter values are equal to the true parameters multiplied by the scale parameter. Although this is irrelevant when calculating the probability of choosing alternative j within one data-set[3], it does confound the comparison of parameters between models or data-sets. Simple Wald tests can therefore not be used to compare estimated coefficients across different experiments. Swait and Louviere (1993) propose a procedure for parameter comparisons between data-sets by using the estimated *ratio* of scale parameters.

A consequence of assuming IID Gumbel distributed errors 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 IIA property provides a computationally convenient choice model, it is unlikely to hold if there is unobserved preference heterogeneity amongst respondents (Louviere et al., 2000). In that case, a CL model specification will lead to biased parameter estimates.

More advanced models are available that have less restrictive assumptions than the CL model. Mixed Logit (ML) – also called Random Parameter Logit (RPL)[4] – models are increasingly used to allow for possible error correlation across alternatives and that account for variation in preferences across individuals by specifying random parameters β_i (Equation 5) (Hensher et al., 2005). In a ML model, vector β_i varies among the population with density function $f(\beta_i|\theta)$. These density functions represent the individual taste differences in the population, with $\boldsymbol{\theta}$ a vector of parameters characterising the density function that captures individual deviations from the mean. A distributional form for $\boldsymbol{\theta}$ needs to be specified by the analyst. Commonly used distributions include the normal, lognormal, uniform or triangular distributions (Hensher et al., 2005, Hensher and Greene, 2003). Triangular distributions with the standard deviation constrained to equal the mean or lognormal distributions can be used if the analyst wants to

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[2] The CL model is appropriate for regressors that vary across alternatives. Some authors incorrectly refer to this model as the multinomial logit model, which is appropriate for alternative-invariant regressors. Any variable that does not vary across alternatives can be included in the CL model by interacting the variable with an ASC (Cameron and Trivedi, 2005: 491-495)

[3] Because all parameters within an estimated model have the same scale parameter

[4] A mixed logit model incorporates a combination of random parameters and latent error components.

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. 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 (Hensher et al., 2005). The introduction of random parameters has the attractive property of inducing correlation across alternatives, thus relaxing the IIA assumption. The random parameter for the *k*th attribute faced by individual *i* is:

$$\beta_{ik} = \beta_k + \sigma_k v_{ik} \qquad k = 1, \ldots, K \text{ attributes} \qquad \text{(Equation 5)}$$

where β_k is the unconditional population parameter of the taste distribution; and v_{ik} are the random, unobserved variations in individual preferences that are distributed around the population mean with standard deviation σ_k[5]. Including this standard deviation implicitly accounts for unobserved individual preference heterogeneity in the sampled population (Hensher et al., 2005).

In the ML model the remaining error ε is still IID distributed over alternatives and individuals, such that the *conditional* probability of observing choice *j* by individual *i* in choice situation *t* (conditional on population parameters $\boldsymbol{\beta}'$ and standard deviation $\boldsymbol{\sigma}'$) can be estimated by the familiar logit model:

$$\Pr(j_{it} \mid \mathbf{X}_{ijt}, \beta_i) = \frac{\exp(\mu \beta_i' \mathbf{X}_{ijt})}{\sum_{j=1}^{J} \exp(\mu \beta_i' \mathbf{X}_{ijt})} \qquad \text{(Equation 6)}$$

As an extension to the ML model, the panel nature of discrete choice data can be exploited using a random-effects model. Panel data models can control for unobserved heterogeneity across the choices made by the same individual, by including an individual specific error term that is correlated across the sequence of choices made by individual *i*. An added advantage of using a panel data model is to control for omitted and unobserved variables (Campbell, 2007). Existing choice experiment studies often fail to fully exploit 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 from the choice sets is the product of the conditional probabilities (Carlsson et al., 2003):

$$S_i(\beta_i) = \prod_t \Pr(j_{it} \mid \mathbf{X}_{ij}, \beta, \sigma) t \qquad \text{(Equation 7)}$$

In a typical CE, this sequence of choices is the number of choice questions answered by each respondent. The *unconditional* choice probability is the expected value of the logit probability

[5] Note that we assume a homogeneous, uncorrelated distribution of individual heterogeneity in this specification.

over the parameter values. This is the integral over all possible values of β_i, weighed by the density of β_i (Hensher et al., 2005):

$$\Pr_i(\mathbf{X}_i, \beta, \sigma) = \int S_i(\beta_i) \cdot f(\beta_i \mid \theta) d\beta_i \qquad \text{(Equation 8)}$$

This model accounts for systematic, but unobserved correlations in an individuals' unobserved utility over repeated choices (Revelt and Train, 1998). In the ML panel specification, parameter vector β_i varies between individuals, but is constant across the choice situations for each individual. Because Equation 8 does not have a closed form solution, the model is estimated using simulated maximum likelihood methods (Hensher and Greene, 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. These appear as $M \leq J$ additional random effects (Greene and Hensher, 2007):

$$U_{ijt} = \beta_i' \mathbf{X}_{ijt} + \varepsilon_{ijt} + c_{jm} \mathbf{W}_{im} \qquad m = 1,...,M \leq J \qquad \text{(Equation 9)}$$

where $\boldsymbol{W}_{im}$ are normally distributed latent effects with zero mean; and $c_{jm} = 1$ 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).

3 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 113km, 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. The region is a popular holiday destination, and Georges Bay is intensively used for recreational activities such as boating, swimming, sailing and recreational fishing. The local population is approximately 2,200 (Census 2006). 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

Figure 1 Location of the George catchment

Bay is located within Moulting Bay. Approximately 3,000 dozen of oysters were harvested in Georges Bay in 2006 (DEWR, 2007).

The quality of the George catchment environment has been identified as an important issue to the local communities (see BOD, 2007, Sprod, 2003, and Rattray, 2001). 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). Although the catchment environment is currently in good condition (Davies et al., 2005), forestry practises, agricultural activities and pollution from sewage and urban areas may threaten the health of the George catchment environment (NRM North, 2008a and 2008b). Local 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.

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

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

4 Survey development and collection

A CE questionnaire concerning the quality of the George catchment environment was developed in collaboration with local decision makers, natural scientists and community members.

The survey material consisted of an introduction letter, a questionnaire booklet and an information poster. The information poster provided information about the George catchment using maps, photos and charts (Appendix 1). Natural resource management in the George catchment, environmental attributes and attribute levels were also described on the poster. The questionnaire was composed of four sections. An introductory section contained questions on visitation and activities in the George catchment, plus a question on the respondent's perception of current river and estuary quality. The next section explained the choice task at hand, followed by the choice questions. A third section contained questions that aimed to elicit respondents' choice strategies and understanding of the survey. The final section consisted of various socio-economic questions.

An extensive literature review and interviews with experts on river health, threatened species, riparian vegetation and estuary ecology underlied the selection of the attributes included in the choice sets[6]. Important attributes were identified and discussed during four focus group discussions organised in Hobart and St Helens in February 2008, and a further four in Launceston and Hobart in August 2008. Two draft questionnaires were also pretesting during these focus group discussions. The Georges Bay estuary was identified by focus group participants as an important attribute in the George catchment. 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, Scanes et al., 2007, and Crawford, 2006), 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 characterize the condition of the George catchment environment: rare native animal and plant species and native riverside vegetation. A payment attribute was included in each choice set, presented as a one-off levy on rates, to be paid by all Tasmanian households during the year 2009.

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 attributes were determined through a combination of literature review, expert interviews, biophysical model predictions and focus group discussions. Attribute levels were identified based on the best available scientific knowledge. The levels of the attributes were

[6] More details about the George catchment questionnaire development are provided in Kragt and Bennett (2008).

defined in a way that was understandable and acceptable to respondents (see Kragt and Bennett, 2008b). Each choice set consisted of a no-cost, no new catchment management base alternative, presented as a likely degradation in catchment conditions in the next 20 years. In this scenario, the environmental attributes would fall to their lowest predicted levels. Two alternative options in each choice set presented improvements in natural resource management and 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 2.

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

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 one-off levy 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 ($) or[7] **0**, 50, 100, 300, 600 ($)

* Currently observed attribute levels in the George catchment in bold.

[7] One of the split samples in this study included higher payments to test whether choices are impacted by the levels of the cost attribute. The results of these tests will be published elsewhere.

The choice sets were created using efficient design techniques. Efficient design approaches aim to maximise the expected precision of the parameter estimates (Carlsson and Martinsson, 2003). A *D-optimal* efficient design aims to minimise the D-error, defined as the determinant of Ω; the asymptotic variance-covariance matrix of a vector of parameters *β.* To calculate the D-error, some information is required about the expected values of *β*. Typically, *prior* values of *β* can be elicited from survey pretests. These prior estimates may not give a precise estimate of the final *β*s. A *Bayesian* design strategy can account for the uncertainty in the prior parameter estimates (Scarpa and Rose, 2008). This simply involves including the distribution over *β* (π_β) into the calculation of the efficiency criterion:

$$\min E_\beta[\{\det(\Omega(\beta,\mathbf{X}_{tj}))\}^{1/K}] = \int_{\Gamma^K} \{\det(\Omega(\beta,\mathbf{X}_{tj}))\}^{1/K}\,\pi_\beta d\beta \qquad \text{(Equation 10)}$$

where *β* is the parameter vector, ***X*** is a matrix of attribute levels in *t* = 1,2,…,T choice sets, with *j* = 1,2,…J alternatives in each choice set; *K* is the number of parameters to be estimated and Γ is the number of draws from the assumed distribution over the parameter estimates π_β. Prior information on the expected values of the parameters *β* was elicited from the results of a survey pretested during the August focus groups. A total of 24 choice sets were generated using a Bayesian *D*-efficient design technique. Some combinations in the choice set design were not feasible, for example because one alternative completely dominated the others in the levels of the environmental attributes but not in costs. These combinations were removed from the choice design, leaving a total of 20 choice sets to be included in the questionnaire. The total number of choice sets was divided into four blocks, so that each respondent was presented with five choice questions.

In order to achieve a representative sample of Tasmanian households, but 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[8] 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 in November and December 2008.

[8] This method involved surveyors to visit randomly selected households within each stratified sampling unit with the request for survey participation. When the 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

5 Results

A total of 1,040 surveys was distributed, of which a total of 586 (56.3%) was returned[9]. There were significant differences in response rates between Launceston and the St Helens and Hobart sub-samples. An important constraint experienced by surveyors was respondents' reluctance to participate in the survey. It became clear that respondents suspected political motives behind the survey, notwithstanding extensive efforts to stress the unbiased and scientific nature of the study. The local community was particular reluctant, leading to difficulties in collecting a sufficient number of surveys for further analysis (Table 3). All information presented was based on scientific data and had been discussed in several focus groups. Nevertheless, respondents' feedback indicated strong disparities between perceived catchment conditions and the current conditions of the George catchment as described in the survey. Particular concerns were raised about the impacts of forestry activities in the catchment. Given the limited number of useable surveys in St Helens and Hobart, no valid conclusion could be inferred about differences in values across populations. A second wave of sampling will be conducted in February 2009 to increase the sample size.

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 515 surveys (Table 3). Because not all respondents answered all the questions, the total number of choice observations available for analysis was 2,021.

Table 3 Number of available surveys by location

Location	Respondents (#)	Response rate (%)
St Helens	34	20.5
Launceston	346	85.0
Hobart	135	40.5
Total	**515**	

In Table 4, 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 the income, education, gender and age distribution in our sample was significantly different from the State average. The sample is therefore not a representative presentation of Tasmanian households. A second sampling round is envisaged in February 2009 to increase the sample size and distribution of socio-economic characteristics. The socio-economic characteristics were not significantly different across subsamples, hence only the means statistics are reported.

[9] Note that a more appropriate measure of response rate would be the rate of acceptance. That is, the percentage of households agreeing to participate in the survey after receiving a door-knock. Unfortunately, this information was not methodically collected by surveyors.

Two attitudinal variables were included in the analysis: level of agreement with the survey information and level of confusion by the choice questions. These variables were measured as respondents' agreement with the statements "I agreed with the information presented on the poster" and "I found answering questions 4 to 8 confusing". Both statements were measured on a 5-point Likert scale where 1=strongly disagree and 5=strongly agree. Of the 493 respondents who answered the attitudinal questions, the majority (strongly) agreed with the information (283), whereas 28 respondents (strongly) disagreed. About 27 percent of respondents were (strongly) confused by the choice task (136 respondents). To account for the impacts of these attitudinal characteristics, agreement and confusion were included in the model specification.

Table 4 Descriptive statistics of George catchment survey sample

Variable	Unit	Mean	Std.	Min	Max
Income	Annual household income ('000 $, before taxes)	76.41	43.85	7.5	210
Education	Respondent education (yrs)	13.36	2.17	8	18
Gender	=1 if respondent is male	0.41	0.49	0	1
Age	Respondent age (yrs)	45.94	14.88	18	89
Agree[*]	Agreement with poster information	3.58	0.74	1	5
Confuse[*]	Confusion by the choice task	2.78	1.02	1	5

[*] Measured on a 5-point Likert scale where 1 = strongly disagree and 5 = strongly agree.

Limdep 9.0 was used to fit conditional logit and mixed logit models, of which the final conditional logit, and two mixed logit specifications are presented in Table 5. A Hausman test showed that the IIA property was violated in a CL model, therefore additional ML models were estimated. To capture the possibility of error correlations between the 'new management' alternatives a common error component was included for the two new-management alternatives (Campbell et al., 2008). The ML models were estimated by simulated maximum likelihood using Halton draws with 500 replications (Train, 2000). The CL and ML1 models threat each choice as a separate observation, whereas the panel specification in the ML2 model accounts for possible error correlation between choices made by the same individual. Given that each individual answered five choice questions, the ML2 model is a more appropriate model specification for analysing CE data.

In all models, an alternative specific constant (ASC) was specified for the base alternative to test whether respondents have a systematic tendency to choose the no-cost, no new catchment management base alternative over the new-management alternatives that can not be explained by observed variables. Socio-economic variables were interacted with the ASC to avoid singularity of the matrix. Respondent's age and additional variables such as sample location, household size and association with the farming of forestry community were not significant in the models and are not included in the final model specifications[10]. For the ML specifications, all the choice attributes were initially included as random parameters to account for variation in respondents' preferences towards the attributes. Several random parameter distributions were tested. Following 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 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.

Except for the insignificant parameter estimates on seagrass in the CL and ML1 models, all parameter estimates have the expected signs. Cost is negative and significant while vegetation and rare species are positive and significant in all model specifications. The significant standard deviation for the random parameters cost, vegetation and species reveal individual heterogeneity in preferences for these attributes. The standard deviation of the seagrass parameter distribution was insignificant. Seagrass was therefore included as a fixed parameter.

An ASC for the base alternative was positive and significant, capturing an inherent tendency for respondents to select the no-cost base alternative over the new-action alternatives. The coefficients on education and income were both negative and significant, indicating that respondents with higher education and incomes are more likely to choose for new management actions. The gender coefficient was positive in the CL and ML1 model, but insignificant in the ML2 model. Not including gender did, however, not improve the model fit and it was decided to include gender for transparency and to allow future testing of possible gender-bias in the results (Ladenburg and Olsen, 2008). Agreement and confusion both have the expected signs, indicating that a higher level of agreement and a lower level of confusion lead to a higher probability of choice for the new-action alternatives.

[10] Results of these models are not reported here but are available upon request from the authors.

Table 5 Conditional and mixed logit model results

Variable	CL – model Parameter	CL – model S.E.	ML1 – model Parameter	ML1 – model S.E.	ML2 – model (panel specification) Parameter	ML2 – model (panel specification) S.E.
Random parameter means						
Costs ($)	-0.003***	0.000	-0.005***	0.000	-0.011***	0.001
Vegetation (km)	0.008**	0.004	0.014***	0.005	0.048***	0.008
Rare species (#)	0.037***	0.003	0.049***	0.006	0.100***	0.009
Random parameter standard deviations						
Cost			0.005***	0.001	0.011***	0.001
Vegetation			0.022	0.016	0.063***	0.009
Rare species			0.042***	0.010	0.092***	0.010
Non-random parameters						
ASC (=1 for base alternative)	4.478***	0.776	5.528***	1.292	8.036**	3.414
Seagrass	-0.000	0.000	-0.000	0.000	0.001**	0.001
Income	-0.006***	0.002	-0.008***	0.003	-0.013*	0.007
Education	-0.246***	0.041	-0.307***	0.068	-0.477***	0.163
Gender	0.242	0.149	0.268	0.188	-0.021	0.555
Agree	-0.688***	0.104	-0.849***	0.193	-1.117**	0.450
Confuse	0.235***	0.074	0.276***	0.104	0.313	0.308
Latent error component (std)			0.170	3.944	2.861***	0.518
Log-likelihood	-1729.97		-1719.78		-1417.36	
Adjusted - ρ^2	0.221		0.225		0.357	
AIC	1.722		1.715		1.426	
BIC	1.750		1.751		1.462	

Note: ***, **, * = significance at 1%, 5% and 10% level.

The ML models include an additional error term to capture unobserved error correlation between the two new-action alternatives. The error component is significantly different from zero in the ML2 model, which indicates heterogeneity across the utilities respondents derive from the new-action alternatives. Accounting for error correlations between individual choices further leads to positive and significant parameter estimates on the the seagrass attribute, where it was negative and insignificant in the other (non-panel) model specifications. Confusion by the choice questions is no longer significant at the 5% level in the ML2 panel model.

The estimated average marginal WTP for a change in each of the attributes in the George catchment survey are presented in Table 6. The 95% confidence intervals were calculated using parametric bootstrapping from the unconditional parameters estimates using 1,000 replications (Krinsky and Robb, 1986). Results from the ML2 model show that respondents are, on average, willing to pay $0.13 for a hectare increase in seagrass area (compared to the base level), $4.46 for a kilometre increase in native riverside vegetation and $9.35 per rare native animal and plant species, *ceteris paribus.*

The estimates are similar between the CL and ML1 model. It appears that, even though the CL model can be rejected in favour of the ML model, there are no significant differences in the WTP estimates between the CL and the ML1 model. The added advantage of the ML1 model is then mostly in revealing preference heterogeneity across choices (Carlsson et al., 2003). However, the ML1 model does not account for repeated choices made by each individual. Allowing for error correlation across choices made by the same respondent in the ML2 model yields different estimates of the marginal WTP. Notably, the willingness to pay for an increase in seagrass area is insignificant in the CL and ML1 model, but positive and significant in the ML2 model. The WTP for native riverside vegetation increases from $2.91 in the ML1 model to $4.46 per km in the ML2 model and the WTP for rare native species decreases from $10.33 to $9.35 per species. The overlapping confidence intervals indicate, however, that these WTP differences may not be significant.

Table 6 Marginal willingness to pay ($) for environmental attributes, 95% confidence interval in parentheses

Attributes	CL model			ML1 model			ML2 model		
Seagrass (ha)	-0.13	(-0.33	0.07)	-0.03	(-0.21	0.13)	0.13***	(0.04	0.22)
Riverside vegetation (km)	2.47**	(0.53	4.42)	2.91***	(1.18	4.65)	4.46***	(3.27	5.66)
Rare species (#)	10.97***	(8.89	13.05)	10.33***	(8.60	12.06)	9.35***	(7.96	10.74)

Note: ***, **, * = significance at 1%, 5% and 10% level.
95% confidence intervals based on the 5th and 95th percentile of the simulated WTP distribution.

A formal test for equality in WTP estimates is the non-parametric convolutions approach proposed by Poe *et al.* (1994, and 1997). This test involves simulating confidence intervals for the *differences* between the marginal WTP estimates. A one-sided significance level can then be calculated as the proportion of negative values in the distribution of differences. A bootstrapping procedure with 1,000 draws was used to calculate the WTP difference between the ML2 and CL models and between the ML2 and ML1 models. The results are reported in Table 7. The equivalence between the marginal WTP estimates can not be rejected for the rare species attribute. However, the estimated WTP is statistically different between models for the seagrass attribute. The WTP for riverside vegetation is significantly different between the CL and ML2 models. When comparing the ML1 and ML2 models, the Poe *et al* test shows less pronounced differences between estimates of marginal WTP for seagrass and riverside vegetation.

Table 7 Testing the equivalence between WTP estimates

	CL vs ML2		**ML1 vs ML2**	
Attribute	90% confidence interval	p-value	90% confidence interval	p-value
Seagrass	(0.45 0.07)	0.011	(0.33 -0.00)	0.040
Vegetation	(3.92 0.05)	0.047	(3.31 -0.27)	0.084
Species	(0.55 -3.65)	0.112	(0.99 -2.91)	0.198

6 Discussion and further research

The experiment described in this paper was aimed at eliciting the values that Tasmanian households hold for protecting natural resources in the George catchment. Several difficulties were encountered while administering the survey in Tasmania. Respondents were concerned about results being used for political purposes (by 'forestry' or 'green' interests). In the local community, the study generated a strong reaction, possibly because the scientific information did not match local perceptions of catchment condition. A second sampling wave will be conducted in February 2009 to increase the sample size.

The results from this study show that Tasmanians hold, in general, positive values for protecting native riverside vegetation and rare native animal and plants species in the George catchment. These results are in line with previous studies on mainland Australia (see, for example, Morrison and Bennett, 2004, and Bennett et al., 2008). A direct comparison between the WTP estimates of different studies is difficult, as every study is contextual and studies tend to use disparate measurement units for the attributes. It can therefore not be concluded that Tasmanians hold higher or lower values for catchment protection than households on mainland Australia households. The George catchment is, like many Tasmanian catchments, in a relatively pristine condition. Future empirical work will be required to reveal whether values estimates from the George catchment survey can be transferred to other catchments in Tasmania or Australia.

There is limited information available on the non-market values that individuals attach to estuary water quality. This study therefore included a seagrass attribute -often used by decision makers as an indicator of estuary water quality- to measure estuary values. The different results for seagrass area between models are surprising. The results from this study show that seagrass in itself may not be a valuable attribute for some respondents. Feedback from local respondents indicated that seagrass beds may be perceived as a ‘nuisance’ by some individuals. This contends the usefulness of seagrass as an indicator of estuary values and warrants further research on how to describe and measure estuary quality in future valuation studies.

Different model specifications reveal significant preference heterogeneity amongst respondents for costs, riverside vegetation and rare species. Furthermore, it is shown that accounting for correlated errors between choices made by the same individual leads to a significantly better model and different value estimates. The evidence presented in this paper strongly suggests that future Australian catchment valuation studies should take individual heterogeneity and the panel nature of choice data into account.

The research reported in this paper is ongoing. Further research will be directed at analysing different survey split samples to test for differences between socio-demographic groups (for example, gender bias) and survey versions (see Kragt and Bennett, 2008a). Possible sources of heteroskedasticity in the random parameters and correlation between random parameters will be explored. It is also proposed to include respondents’ choice strategies in the analysis of the data, as this is expected to provide further insights into respondents’ value preferences.

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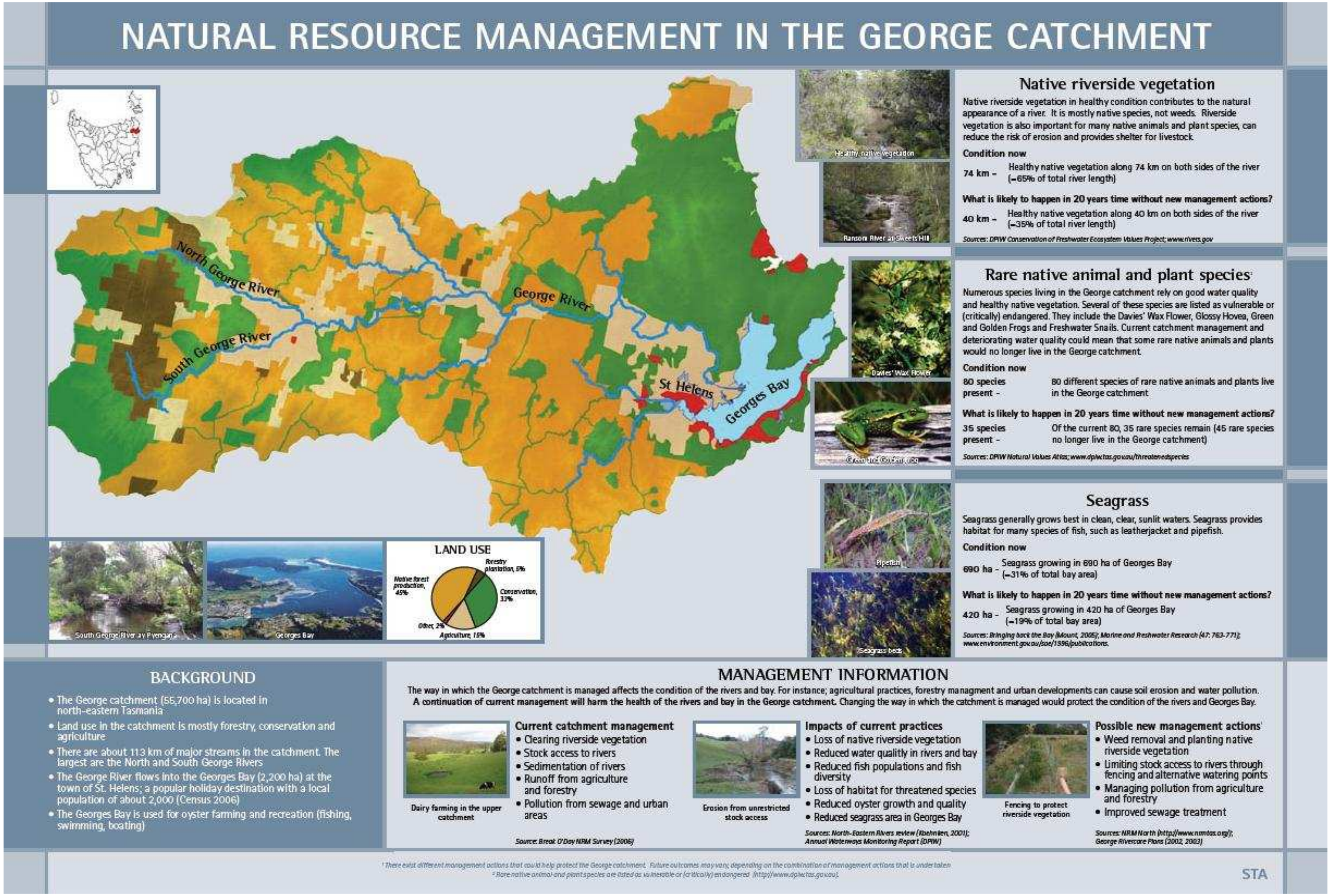
Appendix 1 Information poster included in the George catchment CE



Appendix 2 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)	☐