Comparing models of unobserved heterogeneity in environmental choice experiments

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Abstract

Choice experiments have become a widespread approach to non-market environmental valuation. Given the vast range of public opinions towards environmental management changes, it is desirable that analysis of discrete choice data accounts for the possibility of unobserved heterogeneity amongst the population. There is, however, no consensus about the best way to model individual heterogeneity. This paper presents four approaches to modelling heterogeneity that are increasingly used in the literature. Latent class, mixed logit, scaled multinomial logit and generalised mixed logit (GMXL) models are estimated using case study data for catchment environmental management in Australia. A GMXL model that accounts for preference and scale heterogeneity performs best. I evaluate the impacts of models on welfare estimates and discuss the merits of each modelling approach.

Keywords: Choice Modelling; Econometrics; Random Parameters; Scale Heterogeneity; Unobserved Preference Heterogeneity;

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1 Introduction

Choice Experiments (CEs) are a widely used stated-preference (SP) method to valuing environmental changes. In an environmental CE, individuals are given a series of questions (choice sets), where each question shows the outcomes of alternative (hypothetical) policy scenarios. The outcomes are presented by different levels of attributes that describe the natural resource that the policy aims to manage. By observing the respondents' choices between alternatives, the researcher can observe how respondents trade-off changes in attribute levels. 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 (WTP) or *implicit price* for a change in each of the environmental (non-marketed) attributes.

Conditional logit (CL) models have traditionally been used to analyse discrete choice data (Bennett and Blamey 2001; Scarpa *et al.* 2007). Although the CL model provides a computationally convenient choice model, it is known to be restrictive in its parameter estimation (Kataria 2009). Next to the restrictive Independence of Irrelevant Alternatives (IIA) property, CL models have limited ability to capture individual preference heterogeneity. While socio-economic variables can be included in the specification of the utility function, this approach relies on observable differences between respondents. Recent modelling approaches, such as the mixed logit (MIXL) or latent class (LC) models, relax the IIA assumption and account for unobserved individual heterogeneity in the systematic component of utility (Hensher and Greene 2003). Various authors (e.g. Louviere *et al.* 2002; Louviere and Eagle 2006; Boeri *et al.* 2011) identified the additional importance of accounting for differences in variance between individuals, which requires models that can represent unobserved individual heterogeneity in the random error component of utility. Two models, not yet widely published, can account for scale heterogeneity: the scaled multinomial logit (SMNL) and the generalised mixed logit (GMXL) model.

Notwithstanding the mounting evidence of heterogeneity in the systematic and random components of utility, there are surprisingly few papers that compare the different approaches to modelling unobserved individual heterogeneity. Keane and Wasi (2009) compare the performance of MIXL, LC, SMNL and GMXL models using ten empirical choice data sets for marketed consumer goods. The authors find that GMXL and SMNL model specifications outperform the MIXL and LC models. Greene and Hensher (2010) estimate MIXL, SMNL and GMXL models for a study of transport choices. They find that accounting for scale heterogeneity in the SMNL model is of limited interest in the presence of unobserved preference heterogeneity (accounted for in the MIXL and GMXL models). In the context of valuing environmental goods, Scarpa et al. (2011) investigate the effects of increasing the number of choice alternatives and preference elicitation method (best-worst questions) on the scale parameter for a study of Alpine pastures in Europe. They compare models of scale heterogeneity to models that account for preference heterogeneity and models that include both. They find significant effects of the number of alternatives in the choice context on scale. However, once taste heterogeneity is addressed in a MIXL specification, the scale effect is no longer significant for choice tasks with five alternatives. Best-worst ranking is associated with lower variance than a single ‘most preferred’ choice format. In a study on preference for tap water attributes, Scarpa et al. (2012) conclude that a GMXL model fits their data best, but find issues related to WTP estimation using that model. Christie and Gibbons (2011) also compare models of scale and preference heterogeneity for environmental goods. Similar to Scarpa et al. (2011), They find that preference heterogeneity is more important than scale heterogeneity in their case studies, with MIXL and GMXL models outperforming CL and SMNL models. The authors argue that GMXL models have the potential to improve the rigour of valuation studies for unfamiliar goods, such as environmental goods and services.

The study presented in this paper follows up on the identified need for additional studies that compare approaches to modelling individual heterogeneity (Keane and Wasi 2009; Greene and Hensher 2010). The paper will first clarify various model developments in discrete choice analysis that account for unobserved individual heterogeneity in preferences and/or scale. The case study data used for the study is presented in Section three of the paper. In Section four and five, results of MIXL, SMNL, GMXL and LC model specifications and willingness to pay estimates are presented. The final section concludes.

2 Econometric modelling

CEs have their theoretical foundation in random utility theory that describes utility U_{ijt} that individual *i* derives from choice alternative *j* in choice situation *t* as an observed ‘systematic’ utility component V_{ijt} and a random unobserved error term ε_{ijt} that is independently and identically distributed (IID) over alternatives and individuals:

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

The systematic component of utility is assumed to be a linear, additive function of a vector of explanatory variables $\boldsymbol{x}_{ijt}$, which typically includes the attribute levels of the alternatives and a selection of individual *i*'s socio-economic and behavioural characteristics (interacted with an alternative specific constant-ASC-to avoid singularity of the matrix). These specifications depend on observable differences between individuals that may cause heterogeneity in preferences.

Much recent discrete choice research has focussed modelling *unobserved* preference heterogeneity. Different models have been developed that can account for unobserved preference heterogeneity in either the systematic component of utility, or the random unobserved error term. A number of alternative approaches are considered in this paper and described in the sections below. The way in which each of these models accounts for heterogeneity is summarised in Table 1.

Table 1. Discrete choice modelling approaches accounting for unobserved individual heterogeneity

	Can incorporate unobserved heterogeneity in:	
Model	Systematic component of utility (*taste parameters*)	Random component of utility (*scale parameter*)
LC	Yes (discrete distribution)	No
MIXL	Yes (continuous distribution)	No
SMNL	No	Yes
GMXL	Yes (continuous distribution)	Yes

2.1 Mixed logit models

A model that is now widely used to capture unobserved preference heterogeneity is the mixed logit (MIXL) model. The MIXL model introduces random parameters β_i which vary among the population with density function $f(\beta_i|\theta)$ (Hensher *et al.* 2005). The random parameter for the *k*th attribute faced by individual *i* is:

$$\beta_{ik} = \beta_k + \sigma_k v_{ik} \qquad k = 1,\ldots,K \text{ attributes} \qquad (2)$$

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.[1]

[1] To model the distribution of individual heterogeneity as a function of observed socio-demographic characteristics z_i, we could define the random parameter as $\beta_{ik} = \beta_k + \delta_k z_i + \sigma_k v_{ik}$, where z_i is a vector of choice invariant individual characteristics and δ_k is a vector of parameters that produce the individual specific means.

This model specification implicitly accounts for unobserved individual preference heterogeneity in the sampled population (Hensher, Rose et al. 2005). The density functions $f(\beta_i|\theta)$ 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 and Greene 2003; Hensher, Rose et al. 2005).

In the MIXL model, the *unconditional* choice probability of observing choice *j* by individual *i* in choice situation *t* is the expected value of the *conditional* logit probability (conditional on population parameters $\boldsymbol{\beta}'$ and standard deviation $\boldsymbol{\sigma}'$) over the parameter values. This is the integral over all possible values of β_i, weighed by the density of β_i:

$$E(\Pr_{ijt}) = \int \Pr_{ijt}(\beta_i) \cdot f(\beta_i \mid \theta) d\beta_i \tag{3}$$

Because Equation 3 does not have a closed form solution, the model is estimated using simulated maximum likelihood methods (McFadden and Train 2000).

2.2 Latent class models

The MIXL model specifies unobserved preference heterogeneity as individual deviations from the mean in a continuous distribution. In some instances, the researcher may be more interested in 'clusters' of respondents with similar (but unobserved) preference structures. A model that can capture such unobserved heterogeneity is the latent class (LC) model. In the LC model, the population is divided into a discrete number of classes, where the number of classes is determined endogenously by the data. In the LC model, preferences are assumed to be homogeneous within classes but can vary between classes. The utility that individual *i* derives from choice alternative *j* in choice situation *t* is now:

$$U_{ijt} = \beta_c' \mathbf{x}_{ijt} + \varepsilon_{ijt} \tag{4}$$

where a class specific parameter vector $\boldsymbol{\beta_c}$ is estimated in the LC model. The probability of choosing alternative *j* will be conditional on belonging to a certain class *c*:

$$\Pr(j_{it}|c) = \frac{\exp(\mu_c \beta_c' \mathbf{x}_{ijt})}{\sum_{q=1}^{J} \exp(\mu_c \beta_c' \mathbf{x}_{iqt})} \tag{5}$$

where μ_c is a class specific scale parameter. The error terms are assumed to be independently and identically distributed across individuals and classes with a type I extreme value distribution and scale factor φ. Class probabilities can then be specified by the logit formula:

$$\Pr(c_i) = \frac{\exp(\varphi\gamma_c'\mathbf{z}_i)}{\sum_{s=1}^{C}\exp(\varphi\gamma_s'\mathbf{z}_i)} \tag{6}$$

where $\mathbf{z}_i$ is a vector of choice invariant individual-specific characteristics (e.g. socio-demographic variables); γ_c is a vector of parameters to be estimated n the model; and C is the total number of classes specified by the analyst. One of the parameter vectors γ_c must be restricted to zero to enable model estimation. For a given individual, the choice probability is the expected value of the class specific probabilities:

$$\Pr(j_{it}) = E_c\left[\frac{\exp(\mu_c\beta_c'\mathbf{x}_{ijt})}{\sum_{q=1}^{J}\exp(\mu_c\beta_c'\mathbf{x}_{iqt})}\right] = \sum_{s=1}^{C}\Pr(c_i)\left[\frac{\exp(\mu_c\beta_c'\mathbf{x}_{ijt})}{\sum_{q=1}^{J}\exp(\mu_c\beta_c'\mathbf{x}_{iqt})}\right] \tag{7}$$

This model permits choice attribute data and respondent characteristics to simultaneously explain choice behaviour (Boxall and Adamowicz 2002).

The scale parameters in the LC model deserve some attention. As shown in equations 6 and 7, two scale parameters are estimated in the model, which confound the parameter estimates. The μ_c is a class specific scale parameter, which could theoretically be used to test parameter equivalence across classes (Swait and Louviere 1993). The scale parameter φ in the class membership function is not identifiable (Boxall and Adamowicz 2002).

2.3 Scaled multinomial logit models

The MIXL and LC models can account for unobserved preference heterogeneity in the systematic component of utility. In both model specifications, the scale parameter μ (inversely related to the error variance σ_ε^2) is normalised to enable model estimation. Previous research (e.g. Louviere, Street et al. 2002; Louviere and Eagle 2006) has suggested that such a constant scale of the error distribution may not be appropriate in explaining individual behaviour. Fiebig et al. (2009) describe alternative modelling approaches that can accommodate heterogeneity across respondents in the random component of utility: scaled multinomial logit and generalised mixed logit models.

In the scaled multinomial logit model (SMNL), the error variance $\sigma_{\varepsilon i}$ is allowed to be heterogeneous in the population. In the SMNL model, utility U_{ijt} that individual i derives from alternative j in choice situation t is given by:

$$U_{ijt} = (\beta\sigma_i)'\mathbf{X}_{ijt} + \varepsilon_{ijt} \qquad i=1,\ldots,N;\ j=1,\ldots,J;\ t=1,\ldots,T \tag{8}$$

where β is a vector of population averaged attribute parameters; σ_i is the individual specific standard deviation of the idiosyncratic error term capturing scale heterogeneity; $\boldsymbol{X}_{ijt}$ is a vector of observed, explanatory variables; and ε_{ijt} is a stochastic error that is independently and identically distributed (IID) over alternatives and individuals (Fiebig, Keane et al. 2009).

The individual scaling factor needs to be constrained to be positive. In estimation, this is achieved by using an exponential transformation (Fiebig, Keane et al. 2009; Greene and Hensher 2010):

$$\sigma_i = \exp[\overline{\sigma} + \tau w_i] \tag{9}$$

Here, $\overline{\sigma}$ is the mean parameter in the error variance; τ is a coefficient on the unobserved scale heterogeneity; and w_i is the unobserved individual heterogeneity in scale, which is standard normally distributed. To enable identification of $\overline{\sigma}$, which is not identified separately from τ, σ_i is normalised as $\overline{\sigma} = -\tau^2 / 2$. Larger parameter estimates on τ indicate a higher degree of scale heterogeneity (Fiebig, Keane et al. 2009). The models are estimated using simulated maximum likelihood methods. Some authors have referred to the SMNL model as heteroskedastic choice models, and have defined scale as a function of socioeconomic covariates or choice task features (Scarpa *et al.* 2003; Caussade *et al.* 2005; Scarpa, Thiene et al. 2012)

Most studies that use SMNL models are published by the Institute of Transport and Logistic Studies in Sydney (Keane and Wasi 2009; Beck *et al.* 2011; Hensher *et al.* 2011). These authors, and Greene and Hensher (2010), use CE data of transport choices, vehicle purchasing behaviour, or other marketed goods that are relatively familiar to consumers. To date, only Christie and Gibbons (2011) and Scarpa et al. (Scarpa, Notaro et al. 2011) appear to report SMNL model results for non-marketed environmental goods (biodiversity, coastal defence and Alpine pastures). The present study contributes to the literature in this respect.

2.4 Generalised mixed logit models

A flexible generalised mixed logit (GMXL) modelling approach that can accommodate individual scale as well as individual preference heterogeneity was proposed by Fiebig et al. (2009). The GMXL model specification can thus account for unobserved heterogeneity in both the systematic and the random component of utility. In the GMXL model, utility U_{ijt} is defined by:

$$U_{ijt} = [\sigma_i \beta + \gamma \eta_i + (1-\gamma)\sigma_i \eta_i]' \mathbf{X}_{ijt} + \varepsilon_{ijt} \tag{10}$$

where: σ_I is as in equation 9—the individual specific standard deviation of the idiosyncratic error term capturing scale heterogeneity; η_i is individual specific deviations from the mean, capturing individual heterogeneity in preferences; and γ is a parameter between zero and one, that can capture how the variance of the individual preference heterogeneity varies with scale.

Similarly to the SMNL model, estimating a GMXL model requires a number of normalisations. σ_i is again normalised as $\bar{\sigma} = -\tau^2 / 2$ to enable identification of $\bar{\sigma}$, so that $E[\sigma_i^2] = 1$. Furthermore, to ensure that $\tau \geq 0$, the model is fit in terms of λ, where $\tau = \exp(\lambda)$ and λ is unrestricted (Hensher, Rose et al. 2011). τ is the parameter that captures scale heterogeneity. If τ approaches zero, the GMXL model approaches the ML model (Fiebig, Keane et al. 2009).

Studies that have found the GMXL model to perform well include Greene and Hensher (2010), Hensher et al. (2011), Hensher (2012) and Puckett et al. (2012) for choice experiments in transportation contexts; and Beck et al. (2011), Scarpa et al. (2012) and Kragt (2013) for environmental goods and services.

2.5 Panel data

In the conventional conditional logit model, it is implicitly assumed that the errors across choices made by the same respondent are independent. This is an unrealistic assumption in CE studies, where we observe repeated choices made by the same individual, and recent research suggests that accounting for repeated choice observations has significant effects on the parameter estimates (Scarpa, Willis et al. 2007; Kragt and Bennett 2009).

An attractive feature of the MIXL model is its ability to account for possible error correlations between repeated choices made by the same individual (i.e. account for the panel data nature of discrete choice observations). In a panel format, the conditional probability of observing a sequence of individual choices S_i from the choice sets is the product of the conditional probabilities:

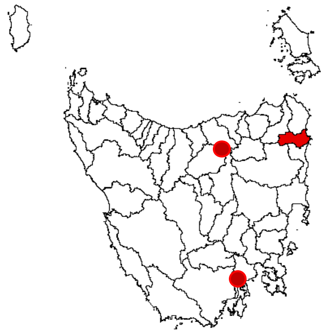
$$S_i(\beta_i) = \prod_t \Pr(j_{it} \mid \mathbf{X}_{ij}, \beta, \sigma)t \tag{11}$$

This accounts for systematic, but unobserved correlations in an individuals' unobserved utility over repeated choices (Revelt and Train 1998).

3 The Choice Experiment

The data for this study comes from a choice experiment on catchment management in the George catchment, Tasmania (Figure 1). The George catchment is a coastal catchment of about 557 km^2 with a local population of approximately 2,200 (Census 2006). The catchment is intensively used for recreational activities. Land use is a mix of native forestry and forest plantations along with dairy farming (DPIW 2007).

Figure 1. Location of the George catchment and survey locations



There are concerns that increased clearing of riparian vegetation, stock access to rivers and streams, and inputs from forestry operations and other human activities will affect water quality and ecosystem health (DPIWE 2005; NRM North 2008).

The CE survey was aimed at eliciting people's preferences for different impacts of natural resource management in the George catchment that could maintain ecosystems. An extensive literature review and interviews local decision makers, natural scientists and community members underlied the selection of the attributes included in the choice sets (Kragt and Bennett 2011). Important attributes were identified and discussed during eight focus group discussions organised in Hobart, Launceston and St Helens. 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 indicator of estuary water quality (seagrass) was therefore included in the questionnaire. Other attributes, identified as important by scientists and focus group participants, were: the number of rare native animal and plant species and the length of 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 reflected the different situations that could occur in the George catchment under various catchment management scenarios. The levels of the attributes were determined through a combination of literature review, expert interviews, biophysical model predictions and focus group discussions. The levels of the environmental attributes were identified based on the best available scientific knowledge at the time. The levels of the cost attribute were based on the maximum WTP for catchment management changes as discussed during the focus groups (Table 2). 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. 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). An example of a choice set is shown in Figure 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 ($) or** **0**, 50, 100, 300, 600 ($)

* 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. The results of these tests are published in (Kragt 2013).

The choice sets were created using a *D-optimal* efficient design. Prior information about the expected parameter values was elicited from the survey pre-tests. A *Bayesian* design strategy was employed to account for the uncertainty in the prior parameter estimates (Scarpa and Rose 2008). A total of 20 choice sets was generated 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 in the catchment. 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 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.

Figure 2. Example choice set in the George catchment CE survey

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	$200	560 ha (25%)	74 km (65%)	50 rare species present (30 no longer live in the catchment)	☐
OPTION C	$400	560 ha (25%)	56 km (50%)	65 rare species present (15 no longer live in the catchment)	☐

4 Results

A total of 1,432 surveys was distributed, of which a total of 933 (65.2%) was returned. Respondents who consistently chose the base alternative because they protested against paying a government levy or because they did not believe the management scenarios were not included in the analysis. This resulted in a total of 832 surveys. Because not all respondents answered all the socio-demographic questions, the total number of choice observations available for analysis was 3,478.

4.1 Descriptive statistics

In Table 3, the descriptive statistics of the sample used in the estimations are presented. A series of χ^2-test were conducted for the sample demographics against the Tasmanian population statistics (ABS 2007). These showed that mean income and age were not significantly different from the State average, but that our sample has a relatively high average education. To account for possible effects of high education on choices, a dummy variable for 'university education' was included in the analysis.

Table 3. Descriptive statistics of George catchment survey sample (n = 832)

Variable	Description	Mean	Std.	Min	Max	n
Education	Respondent education (yrs)	13.39	2.21	8	18	804
Uni	=1 if respondent has at least one year of university training	0.35	0.48	0	1	832
Income	Annual household income ('000 $, before taxes)	74.94	43.84	7.5	210	701
Gender	=1 if respondent is male	0.40	0.49	0	1	811
Age	Respondent age (yrs)	45.67	14.76	18	91	808
Visitation	Number of visits to the George catchment in the past 5 years	5.29	7.93	0	25	831
Envorg	= 1 if respondent is a member of an environmental organisation	0.09	0.28	0	1	823

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

4.2 MIXL, SMNL and GMXL model results

NLogit 5 (Econometric Software 2012) was used to fit a wide range of logit models. In all models, an alternative specific constant (ASC) was specified for the new-management alternatives to test whether respondents have—on average—a systematic tendency to choose the no-cost, no new catchment management base alternative over the new-management alternatives that cannot be explained by observed variables. The utility function was specified as a linear function of choice attributes only, and including respondents' socio-economic characteristics. models were estimated. The socio-economic variables were interacted with the ASC to avoid singularity of the matrix. Initially, a full set of socio-economic characteristics was included in the analysis. Respondent's age and additional variables such as sample location, household size and visitation were not significant in the models and as such are not included in the models reported here. Although the models with socio-economic variables have a slightly better fit than their attribute-only counterpart, the change in log-likelihood and information criteria is very small. This supports recent practice in discrete choice modelling where models are only estimated on their environmental attributes (see, e.g., Balcombe and Fraser 2011; McNair *et al.* 2011; Mørkbak *et al.* 2011; Broch and Vedel 2012; Scheufele and Bennett 2012).

All models were estimated by simulated maximum likelihood using Halton draws with 500 replications (Train 2000). Results of the MIXL, SMNL and GMXL models are presented in Table 4. In the MIXL model, individual preference heterogeneity is accounted for orated by specifying the choice attributes as random parameters (i.e. heterogeneity in the systematic component of utility). Following Greene *et al.* (2006), a constrained triangular distribution was used for the random cost parameter, to ensure a negative sign on the cost parameter. A normal distribution was defined for the environmental attributes.

In the SMNL model, individual heterogeneity is incorporated in the random component of utility (heteroskedastic scale). The GMXL model accounts for heterogeneity in both the random and the systematic component of utility. The GMXL weighting parameter γ was freely estimated in the model without socio-economic characteristics, yielding a value of one. This weighting parameter was subsequently restricted to one in the GMXL model with socio-economic variables to facilitate model estimation.

Comparing first the log-likelihoods and the adjusted ρ^2 goodness-of-fit measures between models, it is evident that the MIXL and GMXL models—which account for preference heterogeneity in the systematic component of utility—provide a better fit on this data-set than the SMNL model that only incorporates heterogeneity in the random error term.

From the SMNL and GMXL models, the significance of the variance parameter in scale (τ) implies that there is significant heterogeneity in scale across respondents. Overall, the GMXL model that incorporates both random parameters and scale heterogeneity performs best. The weighting parameter (γ) in the GMXL model is not significantly different from one. As explained by Fiebig et al. (2009), this parameter governs how the variance of unobserved preference heterogeneity varies with scale in the GMXL model. A value of one means that in this data-set, the standard deviation of η_i is independent of the scaling of β (Fiebig, Keane et al. 2009). An alternative interpretation of this is that the random distribution in individual preferences may have different means but equal variances (for this data-set) (see also Scarpa, Thiene et al. 2012).

All parameter estimates on the choice attributes have the expected signs. Cost is negative and significant while seagrass, vegetation and rare species are positive and significant. The significant standard deviations for the random parameters in the MIXL and GMXL models show the individual heterogeneity in preferences for the choice attributes.

Table 4. MIXL, SMNL and GMXL model results – without (1) and with (2) socio-economic characteristics

	MIXL-1			MIXL-2			SMNL-1			SMNL-2			GMXL-1			GMXL-2		
Variable	Parameter		S.E.	Parameter		S.E.	Parameter		S.E.	Parameter		S.E.	Parameter		S.E.	Parameter		S.E.
Attributes parameter means																		
Costs	-0.011	***	0.001	-0.011	***	0.001	-0.009	***	0.001	-0.008	***	0.000	-0.018	***	0.001	-0.019	***	0.001
Seagrass	0.002	***	0.000	0.002	***	0.000	0.001	***	0.000	0.001	***	0.000	0.002	***	0.001	0.004	***	0.000
Vegetation	0.044	***	0.006	0.043	***	0.006	0.037	***	0.006	0.032	***	0.003	0.063	***	0.008	0.038	***	0.005
Rare species	0.102	***	0.007	0.100	***	0.007	0.100	***	0.007	0.085	***	0.004	0.130	***	0.011	0.140	***	0.008
Random parameter standard deviation / limits of triangular																		
Costs	0.011	***	0.001	0.011	***	0.001							0.018	***	0.001	0.019	***	0.001
Seagrass	0.005	***	0.001	0.005	***	0.001							0.006	***	0.001	0.003	***	0.001
Vegetation	0.073	***	0.006	0.073	***	0.006							0.053	***	0.008	0.049	***	0.007
Rare species	0.109	***	0.007	0.109	***	0.007							0.102	***	0.010	0.078	***	0.007
Non-random parameters																		
ASC	1.831	***	0.256	-0.668	*	0.380	2.159	***	0.346	-0.066		0.363	2.603	***	0.254	0.813	***	0.297
Income				0.012	***	0.004				0.017	***	0.006				0.010	***	0.003
Env-org				1.826	**	0.818				8.719	**	3.698				2.431	***	0.938
Uni degree				0.720	*	0.368				1.461	***	0.551				0.587	*	0.316
τ							1.307	***	0.046	1.210	***	0.039	1.105	***	0.074	1.564	***	0.058
σ_i (sample mean)							0.944			0.819			0.978			0.934		
σ_i (sample st.dev.)							1.553			1.438			1.323			2.093		
γ													1.00	***	0.112	1.00		fixed
Log-likelihood	-2496.1			-2480.3			-2903.4			-2879.3			-2425.33			-2423.92		
McFadden pseudo-ρ^2	0.347			0.350			0.240			0.245			0.366			0.365		
AIC	5008.2			4982.6			5818.7			5776.6			4868.7			4871.8		

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

Now consider the models that include socio-economic variables. The ASC becomes insignificant if income, membership of an environmental organisation, and university education are included in the utility function for the MIXL and SMNL models. The positive estimates on the socio-economic variables indicate that respondents with higher incomes, who are a member of an environmental organisation, and have a university degree are more likely to choose the environmental management alternatives over the no-change base alternative. Although the models with socio-economic variables have a slightly better fit than their attribute-only counterpart, the change in log-likelihood and AIC is very small. This supports the recent practice in discrete choice modelling where models are only estimated on their environmental attributes (see, e.g., Luisetti *et al.* 2011; Mørkbak, Christensen et al. 2011; Broch and Vedel 2012; Scheufele and Bennett 2012).

4.3 Latent class model results

Because of its increasing popularity (Beville *et al.* 2012; Broch and Vedel 2012; Greene and Hensher 2012), latent class (LC) models were also estimated for this study. The main difference with MIXL models is that the LC model specifies unobserved heterogeneity as a discrete, rather than continuous distribution. A great number of LC model specifications were estimated. Following previous studies (Boxall and Adamowicz 2002; Hole 2008; Burton and Rigby 2009; Glenk and Colombo 2011) the results reported here model utility as a linear function of the choice attributes, while class membership is determined by the same set of socio-economic variables used in the MIXL, SMNL and GMXL models.

There are no established statistical tests to select the ‘optimal’ number of classes. The minimum Akaike information’s criterion (AIC), Schwarz Bayesian (BIC) information criterion, McFadden’s ρ^2, and Log-Likelihood values were used to select the number of classes in this model (Table 5). The three-class LC model provides the best model fit on these data. The 4- and 5-class models included classes that had class probabilities of less than 5% which was considered less desirable than a more parsimonious three class model.

Table 5. Comparing the number of latent classes

# classes	LL	Adjusted - $\rho^{2‡}$	AIC	BIC	# parameters (P)
2	-2641.3	0.309	5310.6	5396.7	14
3	-2410.2	0.369	4866.6	5007.8	23
4	-2425.5	0.365	4914.9	5111.8	32
5	-2412.2	0.369	4906.5	5158.8	41

‡ Against an equal market share model with LL=-3821.0; N=3473; AIC=-2(LL-P); BIC=-2LL+[ln(N)*P]

The results for the 3-class LC model are reported in Table 6. In class 1, all environmental attributes are significant at the 5% level, indicating that respondents in this class care about seagrass, native vegetation, and rare species, but that they do not care much about the costs of environmental management actions. None of the socio-economic variables included explain the likelihood of class membership for class 1. Class 2 respondents, on the other hand, appeared to base their choices primarily on the levels of the cost attribute. Conform expectations, respondents with lower incomes are more likely to belong to this class—compared to class 3 respondents. The ASC parameter is significant and positive in class 3, indicating that respondents in that class prefer environmental management over the no-management alternative. The respondents in class 3 were indifferent to seagrass in this study's context, but have positive and significant preferences for vegetation and rare species, and negative preferences towards the cost attribute.

From Table 5, it may appear that the LC modelling provides a better model fit than the MIXL or GMXL models. However, the results show that nearly half of respondents do not make full trade-offs between the environmental attributes and cost (classes 1 and 2: 48.6%). For these classes, willingness to pay measures cannot be estimated. For the purpose of environmental valuation, a GMXL model is therefore the preferred model in this data-set.

Table 6. Latent class model with three classes

Variable	Parameter		S.E.		Parameter		S.E.
Class 1 utility function parameters				*Class 1 membership parameters*			
ASC	0.835		0.588	Constant	-0.227		0.218
Costs ($)	0.001		0.001	Income	-0.000		0.002
Seagrass (ha)	0.001	**	0.001	Member env org	0.450		0.355
Vegetation (km)	0.028	***	0.006	Uni degree	-0.261		0.214
Rare species (#)	0.805	***	0.006				
Class 2 utility function parameters				*Class 2 membership parameters*			
ASC	-0.461		1.067	Constant	-0.774	***	0.278
Costs ($)	-0.023	***	0.007	Income	-0.009	**	0.004
Seagrass (ha)	-0.002		0.001	Member env org	-1.789		1.314
Vegetation (km)	0.001		0.015	Uni degree	-0.513		0.333
Rare species (#)	0.020		0.016				
Class 3 utility function parameters				*Average class probabilities*			
ASC	3.007	***	0.280	Class 1	0.380		
Costs ($)	-0.012	***	0.001	Class 2	0.107		
Seagrass (ha)	-0.000		0.000	Class 3	0.514		
Vegetation (km)	0.014	**	0.006				
Rare species (#)	0.044	***	0.006				

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

5 Willingness to pay estimates

Of particular relevance in an environmental valuation context is respondents' willingness to pay (WTP) for environment changes. Average marginal WTP was estimated using the models that included socio-economic variables (Table 7). The WTP distribution was estimated using parametric bootstrapping from the unconditional parameters estimates using 1,000 replications (Krinsky and Robb 1986). In the LC model, respondents in class 1 and 2 did not trade-off costs with the environmental attributes. Therefore, WTP estimates based on the LC model results could only be calculated for class 3. They are included in the table for illustrative purposes but won't be discussed in the remainder of this paper.

Table 7. Median marginal willingness to pay estimates ($)

Model	MIXL	SMNL	GMXL	LC
Seagrass (ha)	0.215	0.160 ***	0.265 *	NS
	(-0.98 - 1.68)	(0.09 - 0.23)	(-0.16 - 1.08)	
Riverside vegetation (km)	5.052	4.035 ***	2.554	1.756 **
	(-12.4 - 31.5)	(3.15 - 4.98)	(-3.64 - 13.5)	(0.25-3.26)
Rare species (#)	11.92	10.84 ***	9.608 **	5.587 ***
	(-12.8 - 60.47)	(9.45 - 12.4)	(-0.81 - 37.5)	(4.05-7.12)

Notes: ***, **, * = significance at 1%, 5% and 10% level; 95% confidence intervals in parentheses based on the 5^{th} and 95^{th} percentile of the simulated WTP distribution.

The magnitude of WTP estimates is very similar between the MIXL, SMNL and GMXL models, except for the lower estimate on riverside vegetation in the GMXL model. It appears that, even though the GMXL model has a better fit, there are no significant differences in the WTP estimates. A Poe et al. (1994; and 1997) test confirms that WTP differences between models are not significant. This suggests that welfare estimates are not very sensitive to the model specifications, notwithstanding the significant heterogeneity in taste and scale across individuals.

There are, however, notable differences in the significance of WTP estimates. As one would expect, the SMNL model that does not account for preference heterogeneity towards the choice attributes (and thus does not estimate a distribution for the random parameters) has a much smaller confidence interval than the estimates based on the MIXL and GMXL model results. In the GMXL model, the estimates for seagrass and rare species are still significant at the 10% level, notwithstanding the significant individual heterogeneity for these attributes.

6 Discussion and conclusion

The study described in this paper was aimed at investigating different modelling approaches to account for unobserved individual heterogeneity in choice experiment (CE) studies. While there is general agreement that consumer heterogeneity in taste is crucially important in marketing (Keane and Wasi 2009) there are currently few studies that compare the performance of different approaches to modelling heterogeneity, particularly in an environmental valuation context. There is still no agreement about whether individual heterogeneity should be represented by stratifying the population in latent classes, in the systematic component of utility through random parameter estimation, or in the stochastic component as unobserved error variance. This paper contributes to the literature by comparing results from the popular latent class (LC) and mixed logit (MIXL) models with more recently developed scaled multinomial logit (SMNL) and generalised mixed logit (GMXL) models.

This paper aims to explain and test how the MIXL, SMNL, GMXL and LC models account for unobserved individual heterogeneity in taste or scale. A MIXL model outperformed the SMNL model, suggesting that preference heterogeneity towards costs, seagrass area, riverside vegetation, and rare species is more important than scale heterogeneity. A GMXL model specification improved model fit further, and revealed significant scale and preference heterogeneity across respondents. Consistent with findings from other studies (Greene and Hensher 2010; Christie and Gibbons 2011; Hensher, Beck et al. 2011; Puckett, Rose et al. 2012), there is thus clear evidence of significant heterogeneity in scale as well as tastes.

Models were estimates with and without socio-economic variables. It is shown that the models with socio-economic variables only have a marginally better fit than their attribute-only counterpart. This suggests that observable socio-economic characteristics do not explain the difference in choices much better in the presence of scale and preference heterogeneity. Thus, unless a study's objective is to investigate differences between socio-economic classes of respondents (for example, in benefit cost analyses where the aim is to understand respondents' characteristics in more detail), parsimonious attribute-only model specifications may be sufficient.

The MIXL, SMNL and GMXL model results were used to estimate Tasmanians' WTP for seagrass area, riverside vegetation, and rare species in the George catchment. Although the model results revealed significant heterogeneity in taste and scale across individuals, there are no significant differences in welfare estimates. There are, however, differences in the confidence intervals around the WTP estimates—which will be important when values are used in sensitivity or uncertainty analyses. Not surprisingly, the SMNL model that does not account for individual preference heterogeneity has the smallest WTP confidence intervals.

The evidence presented in this paper strongly suggests that future choice experiment studies should specify unobserved heterogeneity in both the systematic and random component of utility. However, the choice of the modelling approach will ultimately vary with the data-set under consideration. For example, although previous studies have found LC specifications to outperform MIXL models (Birol *et al.* 2006; Colombo *et al.* 2009), a 3 class LC model did not perform significantly better for the George catchment data. MIXL specifications model preferences as a continuous distribution. The discrete distribution assumed in LC models may perform well if preferences are more 'lumpy'.

For the present data-set, there were three distinct classes of respondents: those who cared about environmental attributes but not costs, those who cared predominantly about the costs, and those who made full trade-offs between costs and environmental conditions. Given the high proportion of respondents who did not make complete trade-offs between the cost attribute and the environmental attributes, caution is warranted to using these model results when estimating WTP measures. Despite this, LC models may be very useful if the analyst's objective is to better understand the segmentation of preferences in the population.

While the current study presents results of parsimonious, attribute-only model specifications, studies that aim to understand what affects variations in respondents' heterogeneity could explore model specifications that define the distribution of individual heterogeneity as a function of observed socio-demographic characteristics. For example, recent work Beck et al. (2011) and Christie and Gibbons (2011) attempts to further dissect the random component of utility. These studies incorporate response certainty as a determinant in the scale parameter. The authors conclude that accounting for response certainty can improve the reliability and robustness of the results. However, a potential limitation of such work is the correlation between scale and preference estimates in the presence of respondents' uncertainty. Future evidence is needed to disentangle the two effects more fully. It is also advised that more authors report their findings of various modelling approaches to unobserved heterogeneity, particularly when valuing unfamiliar environmental goods, to contribute to building consensus on a preferred approach to modelling heterogeneity.

The research presented in this paper has not been completed. Further work is needed to investigate whether the variance of the error scale, or the scale itself, should be modelled as a function of socio-economic characteristics or choice features. For example, scale variation may occur across the sequence of choices by the same individual (Scarpa, Notaro et al. 2011; Day *et al.* 2012). In that case, individual variance of taste variations is not constant (as implied by the gamma of one), but should instead be modelled as a function of the sequence of choices.

Previous work has suggested that individual preferences for choice attributes are often correlated (Hynes *et al.* 2008; Scarpa, Thiene et al. 2012). An important avenue for further work lies in allowing for correlation across random parameters. Also, models have not yet been estimated in WTP-space. As discussed by, for example, Hensher and Greene (2009) and Thiene and Scarpa (2009), WTP-space models account for both heterogeneity in scale and preferences, and have the advantage of allowing direct control over the WTP distributions (and thus allowing the researcher to directly specify a finite distribution). Estimating models that allow for correlated parameters and models estimated in WTP-space are required to complete the comparisons presented in this paper.

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