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Assessing Respondent's 'Ability to Choose' in Choice Experiments: A Bayesian Estimation of Relative Individual Scale

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Abstract

Free, unregulated economic markets generally fail to provide and protect environmental and natural resources. To overcome this market failure, government intervention is normally required. To ensure that environmental policies are targeted to maximise value for money, data is required on the economic value of environmental and natural resources (HM Treasury, 2003). Environmental economists have, over the past 25 years, developed a suite of techniques capable of measuring the economic value of environmental goods and services, including the choice modelling technique.

An example of an application of the choice modelling technique is recent work by Christie et al. (2006), which aimed to value public preferences for biodiversity enhancements in the UK. Although the research has been widely accepted by both academics and policy makers, a number of unresolved issues were apparent. In particular, no significant differences were found in the value for the different attributes of biodiversity. It is likely that the respondents were a mixture of i) those with similar values for biodiversity elements, ii) those with different values and iii) those with a low ability to choose. A full analysis and understanding of the data requires a method to separate respondents into these groups. Identifying those in group ii will allow a greater understanding of the relative valuation of biodiversity elements. To address this question, sophisticated econometric analysis is required to estimate a respondent's 'ability to choose' between the alternative biodiversity attributes.

In the usual multinomial logit (MNL) analysis of choice experiments the utility parameter coefficients are estimated while fixing the scale parameter at unity. The scale parameter can be interpreted as an estimate of ability to choose. However, with unknown coefficients the scale parameter is not identifiable. The mixed or random parameter logit is a widely used extension to the MNL, where individual random parameters are drawn from a common mixing distribution. This extension allows for random taste variation and unrestricted substitution patterns. We describe an alternative, related approach, modelling individual scale as a random parameter drawn from a common distribution with a known mean of unity. A Bayesian approach is used to estimate these individual random parameters. This approach is also extended to model scale as a function of both a random individual parameter and demographic data. The approach is illustrated using results from two contrasting data sets, the first

evaluating coastal defence options, the second valuing different aspects of biodiversity.

Introduction

Free, unregulated economic markets generally fail to provide and protect environmental and natural resources. To overcome this market failure, government intervention is normally required. To ensure that environmental policies are targeted to maximise value for money, data is required on the economic value of environmental and natural resources (HM Treasury, 2003). Environmental economists have, over the past 25 years, developed a suite of techniques capable of measuring the economic value of environmental goods and services. Early applications of environmental valuation methods tended to focus on goods and services that respondents were both familiar with and had some experience in consuming the goods: for example, the original applications of the travel cost model, contingent valuation and choice experiments were all related to the valuation of outdoor recreation (Clawson and Knetsch, 1966; Davis, 1963; Adamowicz *et al*., 1994). Overtime, and as researchers and policy-makers have become more familiar with the techniques, the methods have increasingly been used to value more complex and often unfamiliar environmental goods and services. A typical example of such an application is recent work by Christie *et al.* (2006) who used choice experiments to value public preferences for various attributes of biodiversity enhancements in the UK. Although the research has been widely accepted by both academics and policy-makers, a number of unresolved issues were apparent. In particular, no significant differences were found between the estimated values for the different attributes of biodiversity. Further, the '*improvements to ecosystem services*' attribute was found to be insignificant in the models. Observations from debriefing sessions indicated that this lack of significance may, in part, be due to a low level of knowledge / understanding of ecosystem services, which in turn resulted in respondents largely ignoring that attribute.

It is likely that environmental economists will continue to push the boundaries of valuation methods to ever more complex and unfamiliar goods and services. For example, Defra have recently initiated a five year research action plan to explore an ecosystems approach to valuation (Defra, 2008). Such extension of environmental valuation methods is likely to be challenging; if not foolhardy. We argue that if such developments are to be made, there needs to be some sort of measure of whether respondents participating in such studies are capable of developing and then revealing their true preferences. In the context of choice experiments, this question is expressed in terms of respondent's 'ability to choose' between choice tasks. In this paper, we utilise a Bayesian, random scale model to evaluate respondent's 'ability to choose' (ATC) in choice experiments.

Aims and objectives

The aim of this study is to explore approaches that can be used to measuring choice experiment respondent's 'ability to choose' (ATC) between choice tasks that aim to value complex and unfamiliar goods. Specific objectives include:

- To develop and compare alternative measures of ATC.
- To apply alternative measures of ATC to two case studies: a complex and unfamiliar good where some respondents are likely to have a low ATC (biodiversity) and a more familiar good where respondents are likely to have well defined preferences (local coastal defence).
- To assess the impact of dealing with ATC on WTP for environmental goods.

The remainder of this paper is organised as follow. In the next section, we outline the theoretical background to the ATC measure, as well as outline our methodological approaches to estimating ATC. Next we outline to case studies in which we apply the ATC measure to. The first case study is the Christie *et al.* (2006) biodiversity study already outlined in the introduction. In this data set, it is expect that, due to the complex and unfamiliar nature of the good, some respondents will have a low ATC. The second dataset relates to a study of the amenity benefits that local residents are likely to gain from various coastal defence options currently being investigated in Borth, West Wales. Initial analysis of this dataset indicates that different groups of respondents from the village have different preferences depending on their personal circumstances. Thus, it is argued that respondents of this second study have clearly defined preferences and therefore a high ability to choose. In the next section, we report the results from the ATC test associated with the two case studies. Finally, we draw some conclusions.

Theoretical background

CE theory: RUT, MNL / RPL models, the scale parameter

Random Utility Theory (RUT; Domencich & McFadden, 1975; Train, 2003) states that, in a discrete choice context, given a set (*J*) of *n* alternatives an individual (*q* of *m* individuals) associates a utility (U_{iq}) with each alternative (*j*) and chooses the alternative with maximum utility. Utility can be decomposed as the sum of two components:

$$U_{jq} = V_{jq} + \varepsilon_{jq}$$

where V_{jq} is the representative (or indirect) utility function conditional on *j* and attributes measured in the experiment and ε_{iq} is an unknown random component including unmeasured attributes. Hence the probability of an individual choosing alternative *i*, is then:

$$P_{iq} = Prob(U_{iq} > U_{jq} \text{ for all } j \text{ where } i \neq j)$$

Under the assumption that ε_{jq} is iid extreme value ($\sim Gumbel(0,\sigma^2)$)this leads to the closed form logit choice probability:

$$P_{iq} = e^{Viq}/\Sigma_j(e^{Vjq})$$

The representative utility is usually specified as a linear function of the observed variables relating to alternative *j*:

$V_{jq} = \beta' x_{jq}$

where β is a vector of parameters to be estimated and x_{jq} is a vector of observed variables for alternative *j*. This specification leads to the multinomial logit (MNL) model:

$P_{iq} = e^{\beta' xiq} / \Sigma_{j(} e^{\beta' xjq})$

Note that relative utility is unaffected if each V_{jq} is multiplied by an arbitrary constant: the same choice is observed. Similarly, the same choice is observed if an arbitrary constant is added to V_{jq}. Both these properties have implications for parameter identification. First, each linear function for each alternative cannot have independent intercept parameters, instead a relative offset has to be estimated to a baseline. This can be achieved by fixing the intercept parameter of the *n-1* alternatives, usually at zero. Second, the parameter scale must be normalized, usually to the scale of utility ($\pi^2/6$), so explicitly:

$B = \beta^* / \sigma$

where σ is the scale parameter and β^* and σ cannot be separately identified. For ease of interpretation we adopt the alternative notation of Breffle & Morey (2000) and define scale *s* as $1/\sigma$. Figure 1 illustrates the effect on choice of different scales.

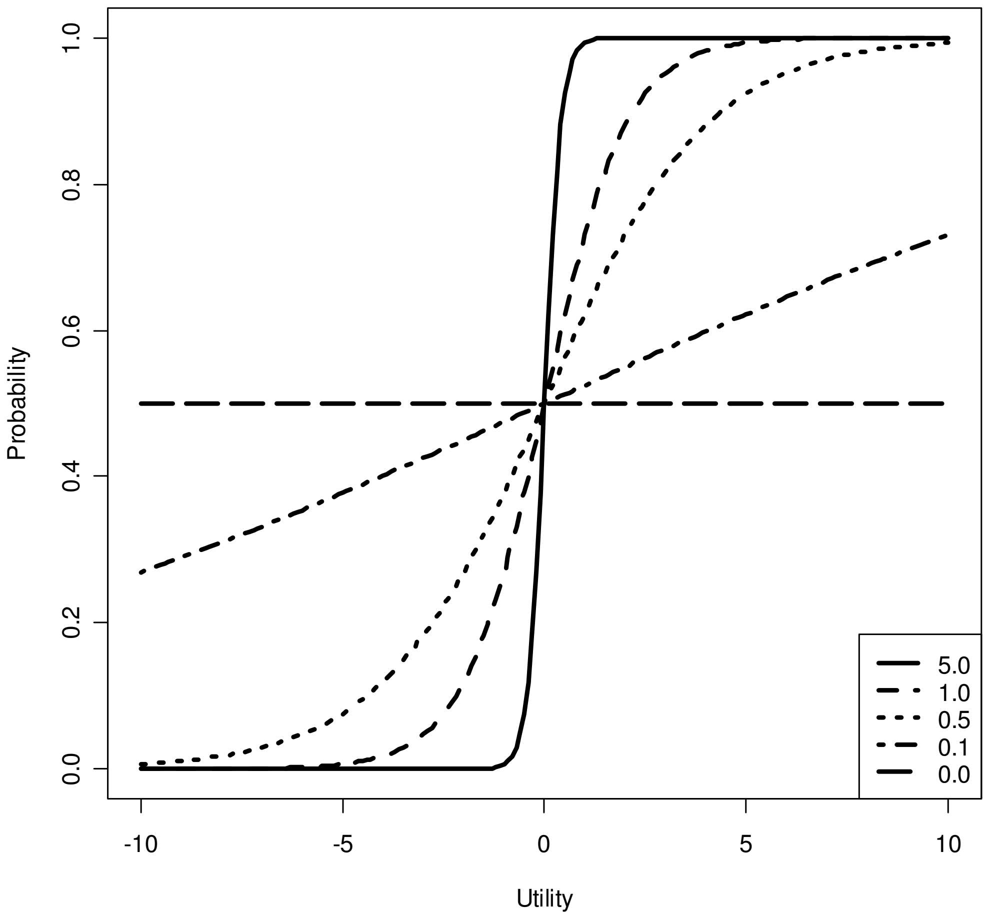

Figure 1. Effect of different scales on response to changing utility. The figure shows an example with two choices A and B. Utility is the relative difference in utility between A and B (x axis) and the y-axis is the probability of choosing A over B. When the difference in utility is zero there is an equal chance of choosing A or B (0.5). As relative utility increases A is more likely to be chosen. Scale mediates the strength of response to changing utility. At large scales a relatively small difference in utility results in large difference in the probability of choosing A over B. At small scales a relatively large difference in utility is required for a large difference in the probability of choosing A over B. When scale is zero differences in utility have no effect on choice.

The well known limitations of the MNL model are that it does not allow for random taste variation, unrestricted substitution patterns and correlation in unobserved factors over time. These restrictions can be overcome by use of the mixed or random parameter logit (RPL) model, which, assuming utility as a linear function, has the following specification:

$$P_{iq} = \int [e^{\beta' xiq} / \Sigma_{j(} e^{\beta' xjq})]\, f(\beta)\, d\beta$$

where $f(\beta)$ is a density function. This specification is very general; the form of the density function must be decided. Common examples are normal, log-normal, triangular or uniform. A very simple illustration can be made with an intercept only model of utility, if the intercept parameter (β_0) has a normal distribution, then:

$V_{1q} \sim N(\beta_0, V)$

where β_0 and V are the mean and variance parameters of the normal distribution and must be estimated. The model structure is therefore hierarchical: individual random parameters are drawn from a function for which the distribution parameters are also estimated.

Identification of individual scale parameters as an indicator of ATC

As described above the scale parameter is not identifiable in a MNL and RPL models where unknown parameters also to be estimated. However, using a random parameter approach it is possible to estimate *relative* individual scale. That is rather than allow β to vary among individuals, assume that β is common and allow error variance, σ^2, to vary among individuals (Breffle and Morey, 2000). This approach estimates how decision-making noise varies among individuals. The approach can be achieved by estimating the individual level random parameter s_q drawn from the normalising distribution $f(s)$. Individuals with relatively large s_q will have relatively small amounts of noise and the model will predict their decisions well. In contrast individuals with small s_q will have relatively large amounts of noise and the model will predict their decisions poorly. To make the link with the RPL model explicit, estimating s_q as a random parameter is equivalent to scaling β by a constant proportion (b_q) for each individual. Therefore, in many cases, a random scale model is a restricted version of a RPL model. However, assuming a normal distribution for β places no constraints on the sign of s_q, where b_q is opposite sign and with a magnitude greater than β s_q will be negative. Note also that in the random scale parameter case (however estimated), individuals with higher scale contribute more to the parameter estimates, scale effectively acts as a weighting coefficient.

While mathematically the distinction between a random scale and a RPL model is clear the philosophic differences should also be emphasised. The RPL approach models differences among individuals as individual specific heterogeneity in the utility of alternatives. The random scale approach implicitly assumes a common utility but differing individual noise when choosing between alternatives. An interpretation of this noise is ability to choose (ATC). When noise is high (scale is low) ability to choose is low, when noise is low ability to choose is high.

Bayesian approach

The modelling in this paper uses a Bayesian (see e.g. Gelman et al., 2004, Rossi et al. 2006) rather than classical approach. The philosophical difference between Bayesian and classical statistics is that prior belief is explicitly included in the model and updated with observed data. However the Bayesian approach is used here largely for convenience as it allows the relatively straightforward estimation of individual parameters and avoids many of the numerical difficulties of a classical approach (see Chapter 12, Train, 2003). In the Bayesian approach parameters of $f(\beta)$ (or $f(S)$) are termed hyperparameters to distinguish them from individual random parameters. The modelling here used diffuse, uninformative, priors thereby specifying a lack of prior knowledge.

Methods

As discussed above, we aim to apply the ATC tests on two choice experiment datasets. The first dataset relates to the Christie *et al.* (2006) biodiversity study. Here, due to the complex and unfamiliar nature of the good, we suspect that respondents had a low ATC. The second dataset relates to local resident's values for the amenity benefits associated with different proposed coastal defence options at Borth in West Wales. Initial analysis of this dataset suggests that different groups of respondents in the Borth study had significantly different values; which were largely dependant their personal circumstances. Given these observations, and the fact that the coastal defence options were familiar (and relevant) to respondents, we suspect that respondents of the Borth study generally had a high ATC. We now provide a brief overview these two case studies.

Biodiversity valuation

The aim of the biodiversity study was to develop an appropriate framework that will enable cost-effective and robust valuations of the total economic value of changes to biodiversity in the UK countryside. The attributes for the choice experiment were designed following a review of ecological and economic literature, as well as a series of developmental focus groups. A key finding from the focus groups were that public understanding of the term biodiversity is generally low. However, the public did develop a do have the capacity to understand the concepts of biodiversity if described in layman's terms. Furthermore, it was clear that the way in which the public consider biodiversity was different to the way in which ecological experts consider biodiversity. Based on evidence gathered in the development stages, five biodiversity attributes were identified for the choice experiment, including a monetary attributes relating to increases in taxation. The four biodiversity attributes investigated were:

- *Familiar species of wildlife*. This attribute was described to include the concepts of charismatic, familiar (recognisable) and locally symbolic species. Three levels of this attribute were presented: protection of rare familiar species, protection of rare and common familiar species, and the status quo (continued decline).
- *Rare, unfamiliar species of wildlife*. This attribute focused on those species that are currently rare or in decline which are unlikely to be familiar to members of the public. The three levels of this attributes included: the slow down of decline of rare unfamiliar species, the recovery of populations of rare unfamiliar species and the status quo (continued decline).
- *Species interactions within a habitat*. This attribute was used to represent the importance of species interactions within a habitat, as well as a proxy for the preservation of ecologically significant species such as keystone and umbrella species. Levels of provision of this attribute included: habitat restoration, habitat re-creation and the status quo (continued decline).
- *Ecosystem processes*. Ecosystem processes focused on biodiversity's role in preserving the health of ecosystem processes. Levels of this attribute included: preservation of ecosystem processes that directly affect humans, preservation of all ecosystem processes, and the status quo (continued decline).

The choice experiment was administered to 400 household in both Cambridgeshire and Northumberland. During the interviews, information on biodiversity was presented using an innovative 20 minute MS PowerPoint presentation. Further detail of the biodiversity study can be found in Christie et al. (2006) and Christie et al. (2004).

Coastal defence study

The second study utilised a choice experiment to explore people's values of the amenity benefits associated with alternative coastal defence options at Borth, located in West Wales.

The two mile stretch of coastline that runs alongside the village of Borth, west Wales has been defended from the sea since the 1930's. The current sea defence system at Borth includes a series of wooden groynes, a shingle bank, and a low seawall. Although this form of sea defence has proven to be effective in the past, recent inspection of the defences has established a need for substantial improvements. In response to these concerns, the local Council identified various options to repair and upgrade the Borth sea defences, including various variations on: replacing the existing timber groynes; replacing the timber groynes with rock groynes / structures; raising the height of the existing seawall; and importantly for this paper, the construction of a multi-purpose reef. Although all proposed coastal defence options were considered to provide adequate coastal protection from the sea, it was clear that the different options had different amenity benefits associated with them.

In the choice experiment, four coastal protection amenity attributes were identified and defined following consultation with coastal protection experts and local residents.

- Visual appearance of beach
- Height of seawall
- Surf conditions
- Beach conditions for family amenity

Each attribute was specified as either two or three levels of provision, including a status quo level.

In the choice experiment, respondents were provided with a summary of the four amenity attributes, which included relevant photos. In addition to these amenity attributes, a fifth attribute relating to annual increases in local tax over a five year period was also included as the price attribute. The tax attribute was specified according to five levels.
One hundred and twenty Borth residents were interviewed during this research. This represents 22.6 % of Borth households. Analysis of the demographics from our survey with that from the local census data revealed that our sample was representative of the local population.

Modelling relative scale

For each case study models were estimated using OpenBugs (Thomas et al., 2006) using diffuse, uninformative priors ($\sim N[0,\ 1x10^6$ for coefficient parameters and $\sim gamma[0.001,\ 0.001]$ for variance parameters). OpenBugs is a Bayesian modelling environment and implements Gibbs and Metropolis-Hastings algorithms for sampling parameter posterior distributions. Individual scale, s_q, was estimated by three alternative approaches. i) using a RPL formulation scaling β by a constant proportion, ii) estimating hyperparameters of *f(s)* constrained to a constant normalising mean and iii) for *f(s)* fixing s_q for one individual and estimating s_q for the remaining *m-1* individuals. The latter two methods require explicit specification of the form of *f(s)* and for method ii) *E[f(s)]* must be a constant. A natural choice for *f(s)* is a lognormal distribution which ensures that all values of s_q are positive. For the lognormal distribution $E[Log\text{-}N(\mu, \sigma^2)]=1$ if $\mu=-\sigma^2/2$, hence σ^2 was estimated while μ was fixed at $-\sigma^2/2$ for method two. (Note that Breffle and Morey (2000) also used a lognormal distribution but constrained $\mu=0$ resulting in $E[f(s)]=exp(\sigma^2/2)$ and normalisation varying over σ^2.) Figure 2 illustrates the sampling structure graphically. The results from method three were expected to be the same as method two once the results were rescaled but method three has possible numerical and computational advantages especially when including demographics.

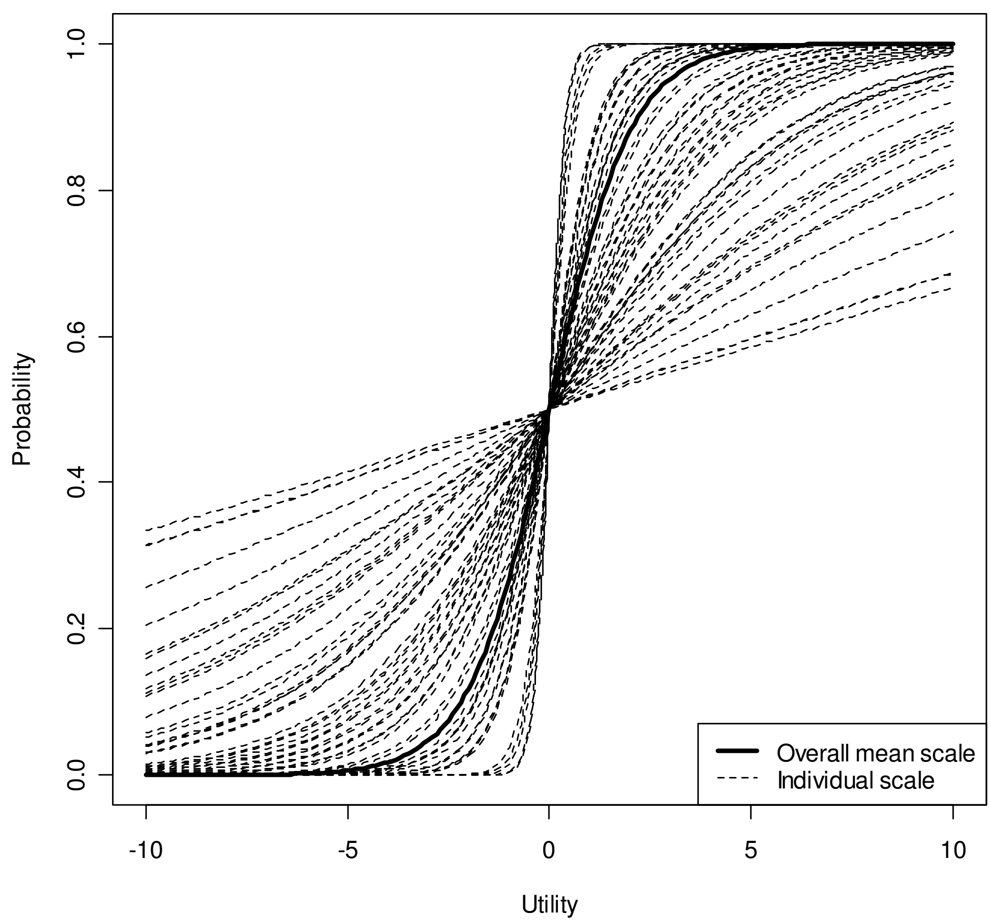

Figure 2. Illustration of the scale sampling procedure. Individual random scale parameters are drawn from a scale distribution with mean 1. In this case relative scale for 50 individuals (dotted lines) are drawn from a log-normal distribution with mean -0.66 and standard deviation 1.25 (heavy line)

For each approach individual demographic information was included in three ways. i) the models were run neglecting demographic information, ii) demographic information was included in the utility function and iii) individual scale was modelled as a function of a random component for each individual plus a demographic component.

For numerical reasons (to improve convergence), continuous data were standardised by subtracting the mean and dividing by the standard deviation. For each model run three chains (from different starting points) of 50,000 posterior draws were run and the first 25,000 draws discarded to ensure chain convergence. The OpenBugs over-relax algorithm was used for each iteration to reduce auto-correlation between draws. Summary statistics were calculated from these chain output with each chain being thinned by a factor of 10 (i.e. every 10th draw was retained). For the fixed individual methodology parameter estimates and individual scales were normalised using the mean of individual scale.

Results

While the Bayesian methodology avoids many of the problems of a maximum likelihood approach numerical and computational problems were encountered while estimating the models. The maximum double precision number on a Windows 32 bit computer is 1.80×10^{308} which on the log scale is 709.8. Hence, the multiplicative effect of individual random scale can result in this maximum being exceeded. To reduce the possibility of this event, the log-normal distribution was assigned a lower limit of 1/50 and an upper limit of 50. In addition, individual utilities exceeding 300 were censored and these draws discarded. Model estimation was slow, taking roughly 26 hours for the biodiversity data including demographic data (the slowest case).

For both case studies including random scale parameter improved model fit (Tables 1, 2). The Bayesian fixed scale results were very similar to the classically estimated multinomial-logit model results (data not shown). The fixed log-normal and fixed individual methods produce similar results (within sampling error of each other). However, standard errors for the fixed individual methodology were generally higher than for fixed log-normal methodology. RPL parameter estimates differed from the other methods this difference is attributable to the method estimating individual scales to be negative (9/120 for the Borth data; 92/702 for the biodiversity data).

Table 1. Parameters for the coastal defence data. ± standard errors.

Parameter	Bayesian fixed scale	Bayesian RPL	Bayesian fixed log-normal	Bayesian fixed individual
Intercept	-0.84 ±0.14	-1.80 ±0.31	-2.17 ±0.46	-2.60 ±0.98
Visual_2	-0.11 ±0.11	-0.23 ±0.11	-0.43 ±0.13	-0.46 ±0.21
Visual_3	1.00 ±0.15	0.84 ±0.20	1.39 ±0.35	1.70 ±0.80
Wall	-0.015 ±0.10	0.33 ±0.11	0.44 ±0.15	0.48 ±0.20
Surf	0.15 ±0.10	0.11 ±0.09	0.12 ±0.10	0.06 ±0.12
Amenity	0.38 ±0.10	0.35 ±0.10	0.45 ±0.13	0.54 ±0.26
Tax	-0.0084 ±0.0022	-0.0064 ±0.0023	-0.0078 ±0.0029	-0.0087 ±0.0047
Log-likelihood	-891	-794	-799	-799

Table 2. Parameters for the biodiversity parameters. ± standard errors.

Parameter	Bayesian fixed scale	Bayesian RPL	Bayesian fixed log-normal	Bayesian fixed individual
Intercept	0.32 ±0.09	-1.58 ±0.46	-0.40 ±0.22	-0.28 ±0.27
eco_2	0.70 ±0.07	0.81 ±0.26	1.22 ±0.16	1.17 ±0.30
eco_3	0.58 ±0.07	0.34 ±0.14	0.42 ±0.15	0.49 ±0.20
fam_2	0.73 ±0.07	0.79 ±0.25	1.24 ±0.14	1.18 ±0.29
fam_3	0.91 ±0.07	0.98 ±0.30	1.61 ±0.17	1.52 ±0.37
hab_2	0.62 ±0.06	0.65 ±0.20	0.95 ±0.12	0.93 ±0.24
hab_3	0.66 ±0.07	0.62 ±0.20	0.96 ±0.13	0.95 ±0.26
rar_2	0.21 ±0.06	0.32 ±0.11	0.51 ±0.12	0.47 ±0.15
rar_3	0.83 ±0.09	1.17 ±0.36	1.76 ±0.23	1.65 ±0.41
Tax	-0.0035 ±0.0002	-0.0037 ±0.0011	-0.0066 ±0.0006	-0.0063 ±0.0015
Log-likelihood	-3152	-2412	-2687	-2687

On a monetary scale (Tables 3, 4) parameter estimates follow a similar pattern to those in Tables 1 & 2. Parameters estimated using the fixed log-normal and fixed individual methods are very similar but different from those estimated using the RPL method.

Table 3. Coastal defence parameters on monetary scale

Parameter	Bayesian fixed scale	Bayesian RPL	Bayesian fixed log-normal	Bayesian fixed individual
Intercept	99.60	283.05	279.77	298.12
Visual_2	12.60	36.06	55.42	53.16
Visual_3	-119.15	-132.02	-178.94	-194.27
Wall	1.75	-51.38	-57.36	-55.09
Surf	-18.29	-16.54	-14.91	-6.67
Amenity	-45.51	-54.31	-58.09	-61.43
Tax	1.00	1.00	1.00	1.00

Table 4. Biodiversity parameters on monetary scale

Parameter	Bayesian fixed scale	Bayesian RPL	Bayesian fixed log-normal	Bayesian fixed individual
Intercept	-92.77	425.99	60.85	44.44
eco_2	-201.29	-219.93	-183.90	-185.85
eco_3	-166.91	-90.78	-63.64	-77.93
fam_2	-210.97	-213.59	-186.46	-188.16
fam_3	-261.22	-264.95	-242.19	-243.18
hab_2	-179.09	-175.63	-142.96	-147.86
hab_3	-188.85	-166.53	-144.23	-151.20
rar_2	-59.21	-85.50	-77.24	-74.75
rar_3	-239.36	-315.59	-265.23	-263.46
Tax	1.00	1.00	1.00	1.00

For the fixed log-normal method the estimated parameters of the scale distribution (Figure 3; $f(S)$) were very similar for both case studies (coastal defence data variance=1.16, biodiversity data variance=1.19). However, there are apparent differences in the distribution of individual scale parameters between the two studies with a cluster of individual scale around 2 for the biodiversity data.

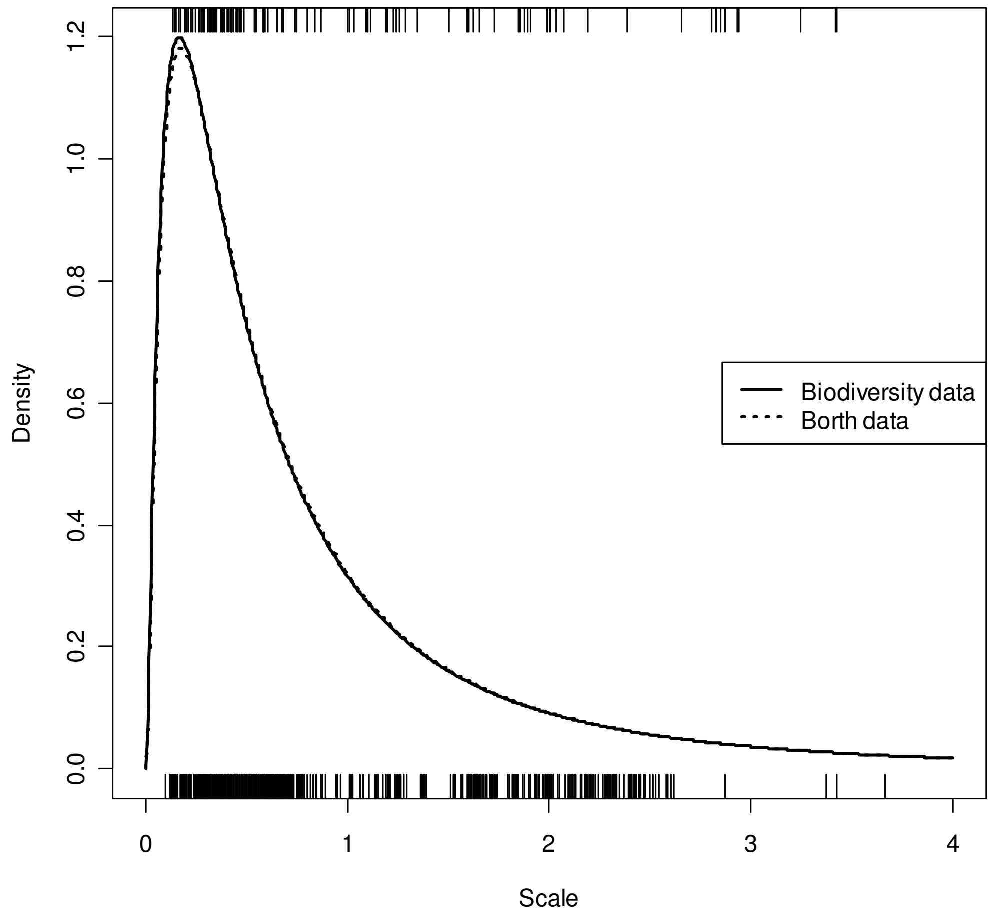

Figure 3. Estimated scale distribution for Biodiversity and Borth data. Rug plots indicate the individual scale parameters for Biodiversity (bottom) and Borth (top).

This apparent bimodality is shown more clearly in a density plot (Figure 4). This result suggests there may be at least two distinct groups of individuals in the biodiversity data, those with relatively high scale and those with low scale. However, finding should be interpreted with caution: the assumption of a log-normal distribution constrains the possible distribution of individual scale. Individual scale will be shrunk away from the right hand tail towards the distribution mode. Confirmation of this result requires further estimation using mixture distributions, allowing much more flexibility in scale distribution.

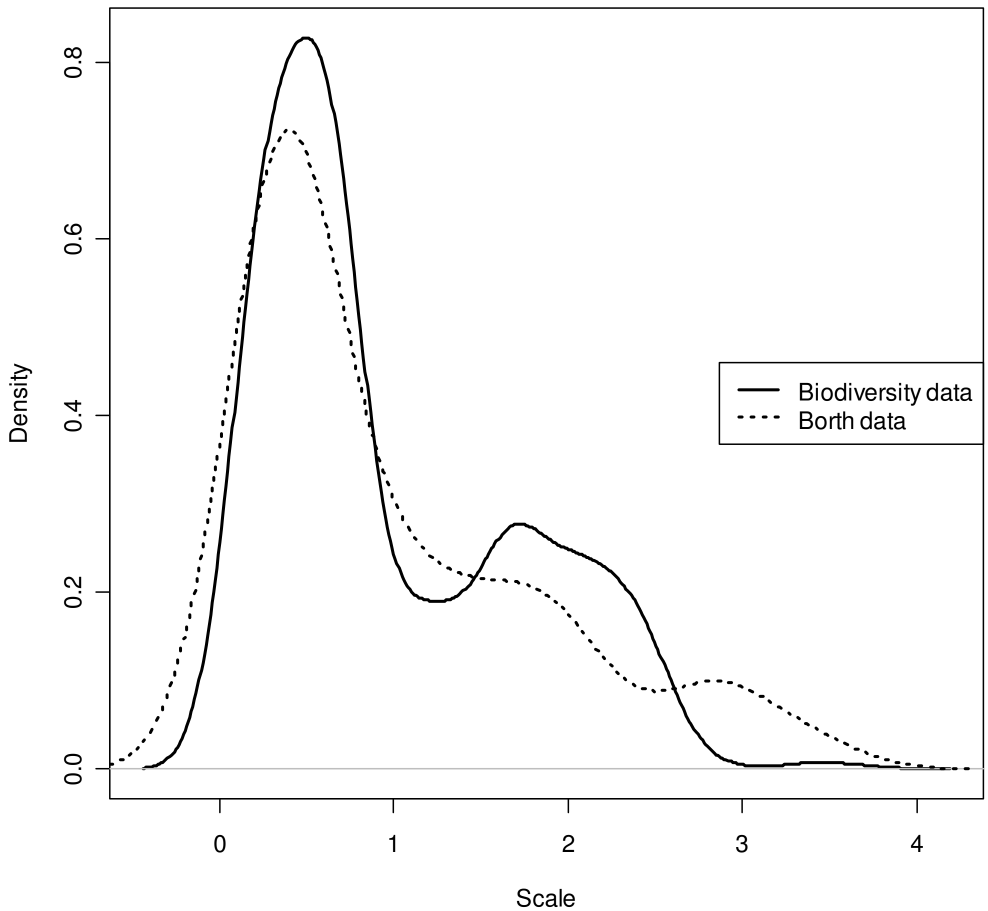

Figure 4. Kernel density plots of distribution of individual scale for biodiversity and Borth data.

Including demographic data, both in the utility function and as predictors of individual scale mad very little difference to the model parameter estimates and individual random parameter estimates. I.e. for both case studies demographic data did not appear to reduce apparent decision noise.

Discussion

As has been previously demonstrated (e.g. Breffle & Morey, 2000), given assumptions about the form of the distribution, it is possible to estimate relative individual scale for choice experiment data. This relative scale can be interpreted as ability to choose between alternatives of different utility. The advantage to this approach is that model parameter estimates are made down-weighting individuals whose decision making is noisy. Alternatively, it would be possible to remove individuals with low scale from the data and reanalyse. The approach has great potential in biodiversity valuation studies where individuals are required to choose between unfamiliar goods and services. This potential is illustrated by a difference in value between types of ecosystems services becoming apparent when individual scale was accounted for.

In our contrasting case studies there appeared to be little difference in the overall individual scale distribution but some evidence for bimodality in the biodiversity data. While it may seem surprising that these very different studies produced very similar results we re-emphasise that the analysis considers only relative *within* study scale distribution. It does not make absolute scale identifiable, i.e. it is possible (and likely) that the coastal defence data had a greater absolute scale than the biodiversity data.

The suggestion of bimodality in the distribution of individual scale suggests that a log-normal distribution may not be always appropriate for scale distributions. The next step in our research is therefore to extend the analysis to a mixture of log-normal distributions. In this way arbitrary (positive) distributions can be modelled. This method is also natural if we consider that individuals are cluster in several distinct groups e.g. those with ability to choose and those with low ability to choose.

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Notes

Returning again to the Christie *et al.* (2006) biodiversity study, it is likely that the respondents could be grouped into three categories: i) those that had an ability to choose and had similar values for biodiversity elements, ii) a second group that had an ability to choose, but had different values and iii) those with a low ability to choose. A full analysis and understanding of choice experiment data requires a method to separate respondents into these groups. Identifying those in group ii will allow a greater understanding of the relative valuation of biodiversity elements. To address this question, sophisticated econometric analysis is required to estimate a respondent's 'ability to choose' between the alternative biodiversity attributes.