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Methods

# The effect of individual ‘ability to choose’ (scale heterogeneity) on the valuation of environmental goods

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ABSTRACT

Environmental valuation methods, such as choice experiments, are increasingly being used to value complex and often unfamiliar environmental goods. A potential risk is that some survey respondents may not be capable of developing and expressing preferences for such goods. The noise from these individuals may then conceal the well-defined preferences of other respondents and affect valuation estimates. We address this problem by estimating a range of models that accounts for scale heterogeneity (which we interpret as a respondent's ability to choose: ATC) and taste heterogeneity. These models are applied to two case studies: amenity from coastal defence and biodiversity. In both case studies, model fit was improved in a scale-heterogeneity multinomial-logit (S-MNL) model (compared to a standard MNL model) suggesting the accounting for ATC (scale heterogeneity) improved preference revelation. A mixed multinomial-logit (MIXL) model outperformed the S-MNL model suggesting that accounting for taste heterogeneity was also important. However, a generalised multinomial-logit (G-MNL) model improved model fit over the MIXL model only for the biodiversity data suggesting that for these data both taste heterogeneity and ATC were important. We conclude that accounting for ATC can improve the reliability and robustness of the results when valuing complex or unfamiliar environmental goods.



## 1. Introduction

Competitive, 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 (European Union, 1992; HM Treasury, 2003; President Reagan, 1981). Environmental economists have, over the past few decades, developed a suite of techniques capable of measuring the economic value of environmental goods and services (Garrod and Willis, 1999). 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 (Clawson and Knetsch, 1966), contingent valuation (Davis, 1963) and choice experiments (Adamowicz et al., 1994) were all related to the valuation of recreational use of the outdoors. As researchers and policy-makers have become more familiar with the techniques, the methods have been used to value more complex and often unfamiliar environmental goods and services (Black et al., 2010; Swanson et al., 2007). For example, recent initiatives to value changes in the provision of ecosystem services associated with biodiversity loss requires survey respondents to have the capacity to understand complex socio-ecological relationships and relate these to their direct, indirect and passive use of ecosystem services (TEEB, 2010). Munro and Hanley (1999) have questioned the credibility and validity of valuation methods that attempt to value complex environmental goods about which respondents may have little prior information, and for which preferences may not be well formed or consistent.

We argue that the extension of valuation to complex and unfamiliar goods requires a measure of whether respondents participating in such studies are capable of developing and then revealing their true preferences. In the context of choice experiments we can distinguish between some individuals differing in preference (taste heterogeneity) and consistency of choice (scale heterogeneity). It seems probable that in the case of unfamiliar environmental goods consistency in choice will vary amongst individuals, and some will have a higher ‘ability to choose’ than others. A respondent's ‘ability to choose’ is likely to be affected by a number of factors including: the respondent's familiarity with the good, i.e. prior and discovered preferences (Fiebig et al., 2010); the complexity of the choice task, i.e. number of attributes and levels in the choice design (DeShazo and Fermo, 2002; Swait and Adamowicz, 2001); and the cognitive ability of the respondent. Existing studies (e.g. Fiebig et al., 2010; Greene and

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Hensher, 2010) suggest that the evidence for the importance of scale heterogeneity in market goods is mixed. In this paper, we utilise two alternative scale heterogeneity models to estimate indicators of a respondent's relative 'ability to choose' (ATC) in choice experiments for non-market goods, and demonstrate how such an approach may be used to improve the reliability of valuation of environmental goods from choice experiments.

### 1.1. Aims and Objectives

The aim of this study is to explore an approach that estimates and accounts for respondent's 'ability to choose' (ATC) in choice experiments. Specifically, we are interested in exploring the impacts that familiarity with the good has on ATC. However, we also argue that the approaches developed to deal with respondents that make poor choices due to unfamiliarity with the good may also be applicable to situations where low ATC is caused by design complexity and low cognitive ability. Specific objectives are:

- To identify a measure of ATC in choice experiments;
- To explore approaches to account for respondents with a low ATC.

The remainder of this paper is organised as follow. In the next section, we outline the theoretical background of the ATC measure and our methodological approaches to estimating ATC. Next we outline the two case studies in which we apply the ATC measure to. We then report the results from the ATC tests associated with the two case studies and explore two approaches to account for respondents with low ATC. Finally, we draw some conclusions.

### 1.2. Choice Experiment Theory: RUT, MNL Models and the Scale Parameter

Random Utility Theory (RUT) (Domencich and 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 ($U_{jq}$) 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 $\varepsilon_{jq}$ is an unknown random component including unmeasured attributes. Hence the probability of an individual choosing alternative $i$ over alternative $j$, is then:

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

Under the assumption that $\varepsilon_{jq}$ is iid extreme value with variance $\sigma^2$ this leads to the closed form logit choice probability:

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

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

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

where $\beta$ 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:

$$P_{iq} = \exp\left(\beta' x_{iq}\right) / \sum_j \exp\left(\beta' x_{jq}\right).$$

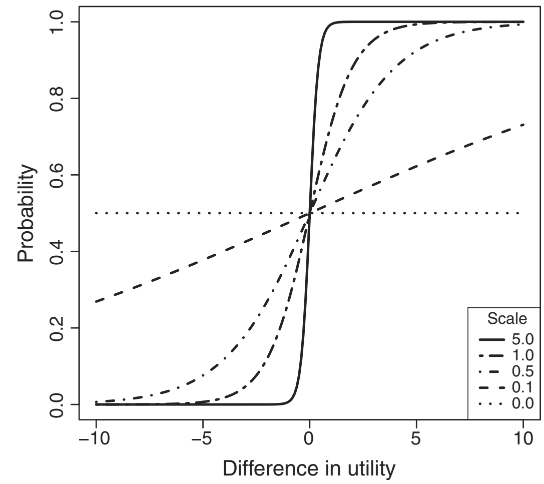


**Fig. 1.** Effect of different scales on response to changing utility. The figure shows an example with two choices A and B. Utility is the relative difference in utility between A and B (x axis) and the y-axis is the probability of choosing A over B. When the difference in utility is zero there is an equal chance of choosing A or B (probability = 0.5). As relative utility of A increases A is more likely to be chosen. Scale (s) 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 (as illustrated by the solid line: scale = 5.0). At small scales (e.g. 0.1) a relatively large difference in utility is required to change the probability of choosing A over B. When scale is zero differences in utility have no effect on choice. Scale therefore characterises a respondent's 'ability to choose' between A and B: the higher the scale the greater the 'ability to choose'.

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 normalised, usually to the scale of utility ($\pi^2/6$), so explicitly:

$$\beta = \beta^* / \sigma$$

where $\beta^*$ and $\sigma$ cannot be separately identified (Swait and Louviere, 1993). For ease of interpretation we adopt an alternative notation and define scale $s$ as $\sqrt{(\pi^2/6\sigma^2)}$. So in the MNL implicitly $s = 1$. If $s$ could be observed for fixed utilities then at low values of $s$, strength of preferences between alternatives is low. Conversely at high $s$, strength of preference is high. Fig. 1 illustrates the effect on probability of choice of different scales.

### 1.3. Relaxations of the MNL Model: MIXL, S-MNL and G-MNL Models

The basic MNL model has a number of well-known limitations including its inability to account for random taste and scale (ATC) heterogeneity. These restrictions can be overcome by the use of the mixed logit (MIXL), scale heterogeneity logit (S-MNL) and generalised multinomial logit (G-MNL) models: see Table 1 for a summary of the key distinctions between these models.

The mixed or heterogeneous logit (MIXL) model can be used to account for random taste variation, unrestricted substitution patterns and correlation in unobserved factors over time. The MIXL model, assuming utility as a linear function, has the following specification:

$$P_{iq} = \int\left\{ \exp(\beta + \eta)' x_{iq} / \sum_j \exp(\beta + \eta)' x_{jq}\right\} f(\eta) d\eta$$

where $f(\eta)$ is a density function of the individual random parameters with a mean of zero. This specification is very general; the form of the