More random or more deterministic choices?

The effects of information on preferences for biodiversity conservation.

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Abstract

For many years, stated preference researchers have been interested in the effects of information on willingness to pay for environmental goods. Within the random utility model, information about an environmental good might impact on preferences and on scale (error variance), both between and within samples of choices. In this paper, we extend the G-MNL model to investigate the effects of different information sets on choices over the management of biodiversity in the UK, looking specifically at moorlands managed for red grouse shooting. Specifically, we make the individual scale parameter a function of observable (dataset-specific) characteristics. Our results show that changing information sets results in significant differences in the mean scale between datasets, and in the variance of scale. Respondents are more deterministic in their choices and show lower within-sample scale heterogeneity in the alternative information treatment. Changes in information provision also effect willingness to pay estimates, reducing the value people place on the conservation of two iconic birds of prey. The methods used will also be of interest to researchers who need to combine choice experiment data sets.

Keywords: choice modelling, biodiversity valuation, information effects, scale heterogeneity, G-MNL models, heather moorland management, raptor conservation.

1. Introduction

Rather early on in the application of Contingent Valuation (CV) to the valuation of environmental goods, researchers found that providing respondents with additional or "new" information on these goods could change measures of willingness to pay. As with goods and services traded in markets, what people know about the characteristics of non-market environmental goods and services, and of substitutes and complements, should co-determine their willingness to pay (Milgrom, 1981; Munro et al., 2002). Changes in the information people hold on a good, including their beliefs in how likely it is to be provided, should change their preferences and values. In hypothetical markets, new information can also influence people's motives to behave strategically in stating their willingness to pay. How information is presented to respondents – its framing – can also change stated WTP (Thaler, 1980; Ariely et al., 2003).

In this paper, we investigate the effects of changing information on stated preferences for biodiversity conservation using a choice experiment. Choice experiments have their basis in random utility theory (Hanemann, 1984; Train, 2009). This postulates that choices depend on a utility function composed of two elements: a deterministic, observable element (V), typically assumed to be a function of choice attributes, and a random or stochastic element, ε . Use of the multinomial logit model to estimate preferences from stated choice data results in preference parameters which are confounded by a scale parameter. This scale parameter reflects the contribution of the deterministic portion of utility to choices relative to the stochastic element. It is likely that this contribution varies across individuals, and that it is sensitive to how informed people are about a good. There is thus as strong a conceptual link between information effects and scale as exists between information and preferences. It is these links which we investigate in this paper.

The paper firstly summarises the literature on information effects in stated preference studies. We then discuss how scale has been modelled in stated choice data, and set out a new approach to represent differences in un-observed preference and scale heterogeneity in combined datasets, namely differences in mean preference and scale coefficients, as well as differences in their variances. The design and implementation of a choice experiment with two information treatments is then described. Results from applying this framework to our study follow, and we conclude with some observations on the implications for future work in stated preference studies of environmental goods such as biodiversity.

2. Information effects in stated preferences for environmental goods

The effects of information about environmental goods on peoples' willingness to pay was one of the early concerns amongst contingent valuation researchers. Munro and Hanley (1999) list eight contingent valuation studies conducted between 1985 and 1992 which investigate the effects of changing information about an environmental good on stated willingness to pay, beginning with Bergstrom et al. (1985). Most of these showed statistically significant effects on mean WTP of changes in information. Munro and Hanley (1999) show formally in an expected utility model that more "positive" information about an environmental good can result in either a fall or a rise in the variance of population WTP, depending on whether high- or low-value individuals are the most responsive to this information[1]. They also show that an individual's WTP is increasing in positive information about the characteristics of a good, implying that mean WTP is also increasing in positive information.

More recent work on information effects in stated preferences has focussed on the type of information provided and how it is provided, as well as the extent of information provided. Aadland et al. (2007) model uncertainty over stated WTP in contingent valuation as being subject to a Bayesian updating procedure. They find that provision of a "cheap talk" script (whereby respondents are told that hypothetical bids are often over-stated) interacts with the value cue implicit in the bid price in a referendum style CV to change stated values. Alberini et al. (2005) explore the impacts of reminding respondents about reasons to vote for and against a proposal, providing concise information to a sub-sample of residents of the Veneto region of northern Italy on the benefits and costs of a project to restore beaches, improve infrastructures and tackle coastal erosion in San Erasmo in the Venice lagoon. They find that this information has no significant effect on willingness to pay except where its interaction with education levels is considered. MacMillan et al. (2006) use CV to obtain values for two environmental goods which differ in terms of familiarity – reintroductions of a bird of prey, and expansion of renewable energy. They find that almost half of respondents change their WTP over successive rounds of information provision (with more pronounced effects for the good with which people were less familiar), and that the number of respondents unsure as to their WTP falls. The effects of "negative" information on wind farms were influenced by how informed people were. However, they also found that opportunities to reflect on information already provided and the hypothetical market, and opportunities to discuss issues with families and friends, were more important than providing new information.

In non-environmental fields, information effects in CV have also been studied. For instance, Protière et al. (2004) undertook a valuation study amongst French citizens of willingness to pay for three health programmes – better heart operation procedures, breast cancer treatments and provision of more air ambulances. They employed three levels of information provision for heart operations, and found WTP was increasing in the amount of information provided. But this increase in information on heart operations (related to days in intensive care, days on a regular ward, and availability of private hospital rooms) also raised WTP for breast cancer treatments and air ambulances. The researchers speculate that this was due to respondents believing that improvements attached to heart operations might spill-over to the other medical investments. Finally, an environmental application which does not use stated preferences but nevertheless considers the type of information provided is Tisdell et al. (2007). They find that provision of information on the conservation status of different tropical animals in Queensland, Australia has significant effects on how much money respondents would like to be allocated to each species from a conservation fund.

Researchers have also considered the importance of the manner in which information is provided in stated preference studies. MacMillan et al. (2006) compared equivalent levels of

[1] Positive information is defined by the authors as information which increases the subjective probability that an environmental good has more desirable attributes and fewer un-desirable attributes.

information provision in a standard individual data collection setting with a valuation workshop setting. Schläpfer (2008) notes that information flows in stated preferences are very much controlled by the researcher, and that "more credible" valuation estimates would result if information could be provided in a similar contested and competitive manner as in public referenda, for example by allowing respondents to access the views of a range of experts or political lobby groups. He argues that this would reduce the tendency of respondents to change their values based on cues which researchers would wish them to ignore, such as the posted price in a referendum-style CV, or the order in which attributes appear in a choice experiment. Hoehn et al. (2010) are also concerned with the way in which information is provided. They compare two designs of choice experiment for wetland restoration which vary only in terms of how information is presented – either in a tabular form (standard practice in a choice experiment) or in a textual form. Based on a theoretical model, they show econometrically that use of a tabular form reduces the use of decision heuristics in the sense that certain presentations of information are easier for respondents to process. This results in a lower error variance in the choice models estimated for the "easier to process" tabular information, relative to the textual information. They also show that when choices are harder due to the use of textual information, respondents ignore more attributes in making their choices. Differences in information presentation also result in differences in estimated preference parameters.

Finally, Christie and Gibbons (2011) are interested in how familiarity with the good effects people's "Ability To Choose" (ATC), as measured by their individual scale parameters. They use data sets from two choice experiments, one on a familiar good (coastal defences at a local beach) and one on a less familiar good (biodiversity conservation). The authors compare models which allow for preference heterogeneity alone, scale heterogeneity alone, and both sources of variation. Their main finding is that accounting for both preference and scale heterogeneity provides the biggest improvement in model fit for the less familiar good (biodiversity) whilst merely allowing for preference heterogeneity gives the best improvement for the familiar good (local coastal defence). Splitting people into "high ATC" and "low ATC" for each good results in large differences in implicit prices. However, the distributions of individual scale parameters are rather similar for both goods. This paper is of particular interest since it links familiarity with ability to choose, or scale. If new information on a good makes choices easier, as well as changing preferences, then allowing for scale variation and variability will be as important, potentially, in understanding the effects of information as allowing for changes in preference parameters and willingness to pay.

3. Modelling preference and scale heterogeneity in discrete choice experiments

As noted above, Christie and Gibbons (2011) link familiarity with a good – and thus the potential impacts of new information – with the scale parameter in the Random Utility Model. This is of particular interest since the modeling of discrete choice data relies on random utility theory to explain choices and thus derive estimates of preference parameters (McFadden, 1974). It assumes that the utility associated with any alternative (choice option) can be divided into a sum of contributions that can be observed by a researcher, and a component that cannot, and hence is assumed random. This formulation of utility function and choice-specific alternatives leads to the conditional multinomial logit model in which observed choices of an individual are used to link the choice alternatives with utility levels. Formalizing, let individual i choose among J alternatives, each characterized by a vector of observed attributes $\mathbf{x}_{ij}$. The utility associated with alternative j is given by:

$$U_i\left(Alternative = j\right) = U_{ij} = \boldsymbol{\beta}'\mathbf{x}_{ij} + \varepsilon_{ij}, \tag{1}$$

where $\boldsymbol{\beta}$ is a parameter vector of marginal utilities of the attributes. Introduction of the error term Ɛ makes it possible to explain why apparently equal individuals (equal in all attributes which can be observed) may choose different options. Random utility theory is transformed into different econometric models by making assumptions about this random term. Assumptions with respect to the random term variance may be expressed by scaling the utility function in the following way:

$$U_{ij} = \sigma\boldsymbol{\beta}'\mathbf{x}_{ij} + \varepsilon_{ij}, \tag{2}$$

where the random component of the utility function is typically assumed to be independently and identically (iid) Extreme Value Type 1 distributed across individuals and alternatives, with the scale coefficient (usually normalized, since σ and $\boldsymbol{\beta}$ cannot *both* be identified) proportional to the inverse of the error term, $\sigma \sim 1/\varepsilon$. This way a Multinomial Logit Model (MNL) is derived, with the following closed-form expression of the probability of choosing alternative j from a set of J available alternatives:

$$P\left(j \mid J\right) = \frac{\exp\left(\sigma\boldsymbol{\beta}'\mathbf{x}_{ij}\right)}{\sum_{k=1}^{J}\exp\left(\sigma\boldsymbol{\beta}'\mathbf{x}_{ik}\right)}. \tag{3}$$

The MNL model implausibly assumes that all respondents have the same preferences (and so the same coefficients in their utility functions, $\boldsymbol{\beta}$). One way of relaxing these assumptions, i.e. allowing for some level of (unobserved) preference heterogeneity and possibly correlations between the alternatives and choice tasks, is the Random Parameters Logit model (RPL, McFadden et al., 2000; Hensher et al., 2003). In RPL the utility function becomes:

$$U_{itj} = \sigma\boldsymbol{\beta}_i'\mathbf{x}_{itj} + \varepsilon_{itj}. \tag{4}$$

Note that parameters of utility function are now respondent-specific. It is assumed that they follow multivariate distribution specified by a modeller: $\boldsymbol{\beta}_i \sim f\left(\mathbf{b} + \boldsymbol{\Delta}'\mathbf{z}_i, \boldsymbol{\Sigma} + \boldsymbol{\Gamma}'\mathbf{z}_i\right)$, with means $\mathbf{b}$ and variance-covariance matrix $\boldsymbol{\Sigma}$. In addition, it is possible to make means and variances of the distributions a function of observable respondent or choice-specific characteristics $\mathbf{z}$.

Finally, one can control for both preference and scale heterogeneity of respondents at the same time using the Generalized Multinomial Logit Model (G-MNL, Fiebig et al., 2010). In this model, the utility function takes the form:

$$U_{itj} = \left[\sigma_i \mathbf{b} + \gamma \boldsymbol{\upsilon}_i + (1-\gamma)\sigma_i \boldsymbol{\upsilon}_i\right]' \mathbf{x}_{itj} + \omega_{itj} . \tag{5}$$

Similarly to the RPL model, the coefficients in the utility function are individual-specific ($\mathbf{b}$ represents the population means of the parameters, while $\boldsymbol{\upsilon}$ – individual-specific deviations from these means). Unlike in the RPL, however, the scale coefficient is also individual-specific, with $\sigma_i \sim LN(1,\tau)$ or $\sigma_i = \exp(\bar{\sigma} + \tau\varepsilon_{0i})$ with $\varepsilon_{0i} \sim N(0,1)$. Since it is still necessary to normalize scale, we want $E\sigma_i = \exp(\sigma + \tau^2/2)$. This may be achieved by assuming $\bar{\sigma} = -\tau^2/2$. This way the scale is no longer constant across respondents; instead it is assumed to follow a lognormal distribution, with the new parameter τ reflecting the level of scale heterogeneity in the sample. The coefficient $\gamma \in [0,1]$ controls how the variance of residual taste heterogeneity varies with scale.[2] If $\gamma = 0$ the individual coefficients become $\boldsymbol{\beta}_i = \sigma_i(\mathbf{b} + \boldsymbol{\upsilon}_i)$, while if $\gamma = 1$ they are $\boldsymbol{\beta}_i = \sigma_i \mathbf{b} + \boldsymbol{\upsilon}_i$. These are the two extreme cases of scaling (or not scaling) residual taste heterogeneity in the G-MNL model (type I and type II respectively), however, all intermittent solutions are possible.

Accounting for observable scale heterogeneity

It is often useful to allow for systematic differences in scale between observations. Some examples of utilizing observation-specific scale include respondent-specific scale differences, for instance reflecting levels of familiarity with the good which may result in less random choices for some respondents, or choice task-specific scale differences, e.g. due to learning or fatigue which may cause respondent's choices to become more or less deterministic as he has completed more choice tasks. However, by far the most common use for introducing observation-specific scale is accounting for scale differences when two or more datasets – for example, from two different information treatments - are combined. It has long been recognized that if observations from two datasets are to be combined, then accounting for scale differences is necessary (Swait et al., 1993). This is because utility function parameters are confounded with scale and so failing to take this into account (i.e. assuming the scale parameter in two datasets is the same) may lead to biased estimates. Scale may vary across data sets due to differences in sampling or information provided to the respondents. Only after the scale differences have been accounted for it is possible to formally test the equality of utility function parameters and their variances if unobserved preference heterogeneity is allowed for (Hensher et al., 1998).[3]

[2] To assure $\gamma \in [0,1]$ it is usually modeled as $\gamma = \frac{\exp(\gamma^*)}{1+\exp(\gamma^*)}$, and it is γ^* that is estimated.

[3] Many studies compare implicit prices (i.e. ratios of parameters) derived from separately estimated models, as this way dataset-specific scale cancels out. However, this approach leads to the possibility of confounding differences in preferences for the attributes and marginal utility of income (cost). In addition it does not allow to easily test for dispersion of random parameters, if unobserved preference heterogeneity is allowed for. Finally, we note that in the case of unobserved preference heterogeneity, many researchers fail to properly conduct the test

Several methods that allow one to control for scale differences between datasets have been proposed. Ben-Akiva et al. (1990) proposed a procedure to efficiently estimate the scale differences between two data sources. Their procedure simultaneously maximizes a joint likelihood function for observations from two or more datasets. A relative scale factor can be estimated for each type of data (except one which is arbitrarily chosen as the base level; Morikawa, 1989). Bradley et al. (1992); (1994) incorporated the one-step estimation approach of Morikawa and Ben-Akiva into one which can be implemented using a nested logit. They call this approach the *logit-based scaling approach* (Hensher et al., 1993; Bradley et al., 1994). Swait et al. (1993) proposed a sequential scaling approach which allows to combine data from two sources by applying a grid-search over the range of plausible relative scale values and using likelihood-ratio test. This "tedious, but straightforward" procedure results in unique maximum for the log likelihood function, at least for the linear-in-parameters MNL model for which log-likelihood is concave. The *Swait-Louviere procedure* can be used only if the test for substantive parameter differences is non-significant, but still is probably the most commonly used way to test for scale differences between two datasets, at least in environmental economics applications (e.g. von Haefen et al., 2008; Christie et al., 2009; Olsen, 2009; Brouwer et al., 2010). Finally, a number of authors have used the Heteroskedastic MNL (H-MNL) model to explore issues related to observed scale heterogeneity, by including observation-specific covariates of scale (e.g. Hensher et al., 1998; Dellaert et al., 1999; Swait et al., 2001; Caussade et al., 2005). The utility specification of the H-MNL, with covariates of scale entering linearly (Dellaert et al., 1999) is:

$$U_{ij} = \sigma\left(1+\boldsymbol{\theta}'\mathbf{k}_i\right)\boldsymbol{\beta}'\mathbf{x}_{ij} + \varepsilon_{ij}\,, \qquad (6)$$

while by assuming an exponential formulation for the multiplicative scale (Swait et al., 2001) it is possible to drop the 1 and there is no need to assume the scale is strictly positive:

$$U_{ij} = \sigma\exp\left(\boldsymbol{\theta}'\mathbf{k}_i\right)\boldsymbol{\beta}'\mathbf{x}_{ij} + \varepsilon_{ij}\,. \qquad (7)$$

In both cases, the 'effective' scale is a function of $\mathbf{k}_i$ – vector of observation-specific and observable variables. The scale is still normalized, but with respect to the reference group and so it can differ for selected observations (e.g. one of the datasets).[4]

The methods presented above, however, do not allow for unobserved scale heterogeneity, despite a growing body of literature suggesting that modeling of unobservable scale differences may be a significant component in accounting for overall heterogeneity (e.g. Louviere et al., 2002). Once the unobserved scale heterogeneity is allowed, groups of observations (e.g. datasets) can differ not only in

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for equality of mean WTPs, as they do not take the all the information about the empirical distribution of WTPs into account, usually focusing on their means and associated standard errors only, rather than also take the standard deviations (and their standard errors) of the distributions of WTPs into account.

[4] Some less commonly used methods that allow for controlling observed scale heterogeneity include the covariance heterogeneity model (DeShazo et al., 2002), the error components model (Hensher et al., 2008; Savage et al., 2008), modeling Gumbel variance directly by using socio-economic characteristics (Scarpa et al., 2003), heteroscedastic extreme value (Salisbury et al., 2010), or multiplicative errors model (Fosgerau et al., 2009).

terms of preferences (e.g. means of random parameters), preference heterogeneity (e.g. variances of random parameters), and scale, but also with respect to scale heterogeneity (i.e. scale variance). The approach we propose allows to simultaneously take all these differences into account. Our approach in this paper is based on the G-MNL model, which allows one to control for unobserved heterogeneity of preference and scale (Fiebig et al., 2010). We extend it by including dataset-specific covariates in mean scale and in its variance (τ) to combine datasets and control for differences in both – scale, and scale-heterogeneity. This can be achieved by making the individual scale parameter a function of observable (in our case dataset-specific) characteristics $\mathbf{k}$, and at the same time including them as covariates of τ, so that:

$$\sigma_i = \exp\left(\bar{\sigma} + \exp\left(\boldsymbol{\lambda}'\mathbf{k}_{it}\right)\tau\varepsilon_{0i} + \boldsymbol{\theta}'\mathbf{k}_{it}\right). \tag{8}$$

The resulting extension of the G-MNL model is flexible enough to capture observed and unobserved preference heterogeneity, as well as observed and unobserved scale heterogeneity. In what follows we demonstrate how it can be used to combine datasets while controlling for differences in scale and in its variance.

4. Case Study and Survey Design

4.1 Case study

The management of Red Grouse (*Lagopus lagopus scotticus*) in the UK uplands provides an interesting case study of conflicts in biodiversity conservation. Management of moorlands for Red Grouse shooting since the mid 19th Century has led to declines in many species of predators (Newton 1998), since the aim of grouse management is to maximise numbers of birds available for shooting in the autumn. This management involves a mixture of vegetation management (e.g. heather burning) and predator control (Hudson & Newborn, 1998). One particular conflict which has arisen in this context concerns the management of Hen Harriers (*Circus cyaneus*) on sporting estates. Hen Harriers are a medium-sized bird of prey which breed on heather moorlands in the uplands. They are Red Listed due to population declines in the last 200 years (Baillie et al., 2009). Most recent data reveals population decreases on moorland managed for grouse shooting in the Southern Uplands, eastern Highlands and northern England (Sim et al., 2007). Hen Harriers have been protected by law since 1954, but illegal killing has occurred due to the economic costs of Hen Harriers to grouse moor managers.

Economic costs to grouse moor owners arise because harriers prey on grouse (Thirgood et al., 2000), and arguments between the conservation lobby and the sporting estate community have become polarised over time (Redpath et al, 2004; Thirgood and Redpath, 2008). Evidence shows that (i) Hen Harrier densities can increase to the extent that they make management for grouse shooting economically unviable; (ii) illegal killing has resulted in a suppression of harrier populations in both England and Scotland (Etheridge et al., 1997); and (iii) that enforcement of current laws prohibiting lethal control has been ineffective (Redpath et al., 2010). Golden Eagles are often found in Hen Harrier habitat, and are also top predators which have been subject to illegal persecution, particularly in managed grouse moors (Watson et al., 1989; Whitfield et al., 2007). To understand public preferences over the conservation of Hen Harriers on heather moorland, we designed a choice experiment (Hanley et al, 2011). The choice experiment design consisted of four attributes. These were:

- Changes in the population of Hen Harriers on heather moorlands in Scotland. The levels here were a 20% decline (used as the status quo), maintaining current populations, and a 20% increase in the current population.

- Changes in the population of Golden Eagles on heather moorlands in Scotland. The levels here were a 20% decline (used as the status quo), maintaining current populations, and a 20% increase in the current population.

- Management options. These included the current situation, moving Hen Harriers ("MOVE"), diversionary feeding ("FEED") and tougher law enforcement ("LAW"). These levels were included as labelled choices. That is, in each choice card, 4 options were available. One represented the status quo, and then 3 choice columns showed variations in other attribute levels given a particular, labelled management strategy.

- Cost of the policy. We told respondents that "*the **cost** level indicated is the amount of extra tax which a household like yours might have to pay if the government went ahead with that option."* The levels used were £0 (the status quo), £10, £20, £25, and £50. These costs are not linearly associated with any management option, since actual costs are unknown, and since this would create difficulties for estimating the choice model. Cost levels were chosen based on the results of a pilot survey.

Figure 1 gives an example of a choice card. Respondents were asked to carefully consider their budgets and current expenditures in making their choices, and that they should not worry if they did not feel that they had expert knowledge on the issues, but that their opinion was important to government policy making. Six choice cards were given to each respondent. Those respondents who chose the status quo, zero cost option in each choice card were asked why this was, in order to separate out protest bidders from people who did not value Hen Harrier or Golden Eagle conservation in moorlands. Having completed their choices, respondents were asked to read back carefully through these to make sure they were happy with how they had completed these tasks. Finally, a series of socio-economic and behavioural questions were asked, for example including household income, and whether the respondent was a hunter or had ever been hunting. The choice experiment was designed to minimize the determinant of the AVC matrix of the parameters (*D-error*) given the priors on the parameters of a representative respondent's utility function using a Bayesian efficient design (Scarpa and Rose, 2008). The parameters of this distribution were derived from a preliminary model estimated on data available from a pilot study. Pilot surveys were undertaken using in-person surveys of a random sample of Edinburgh households.[5] The final design consisted of 8 questionnaire versions, each with 6 choice cards per respondent.

[5] The design for the pilot study was also generated for D-efficiency, using expert judgment priors.

Two samples were obtained from a random selection of households in Scotland, using a series of mail shots. In each survey, households were contacted, and a 3-stage Dillman procedure followed in terms of reminder letters and new copies of the survey instrument. The surveys differed only in the information provided to respondents. The first survey (study 1), reported in Hanley et al (2011), used an information pack developed solely by the research team, based on existing research findings. We refer to this as “information pack 1”. The second survey (study 2) used an information pack which was re-written by a group of stakeholders engaged in moorland ownership, management and grouse shooting. We refer to this as “information pack 2”. In each case, the information pack covered the following items:

- A description of what we meant by “the uplands” in the UK
- how some uplands areas are managed as grouse moors
- the contribution that grouse shooting makes to the Scottish economy
- the contribution of grouse management to maintaining heather moorlands, rather than allowing moorlands to be converted to rough grassland or plantation forestry.
- A description of the Hen Harrier, including conservation status and threats from illegal persecution.
- A description of Golden Eagles, their conservation status and current threats to the species.
- The three alternatives for moorland management aimed at Hen Harriers are then described: setting up feeding stations, moving eggs and chicks to ensure local populations stay within prescribed quotas, and stricter law enforcement. Respondents were told that each of these alternatives would impose costs on society, for example in terms of extra policing, or labour costs for movement of birds, and that these costs would need to be paid for out of increased taxes.

Given that the biodiversity issues involved in moorland conservation are likely to be unfamiliar to many respondents, we might anticipate that differences in information provided might well impact on their choices. Across the two surveys, the most significant differences between how these items were relayed to respondents were as follows:

1. Moorland management is depicted as more beneficial in Information Pack 2 (recall that this was edited by the stakeholder group):

- In the box on red grouse in the second survey it is stated that “…management activities can benefit other species of birds such as lapwings and curlew”. These additional benefits of land management are not referred to in the first survey.

- In the box on red grouse in the second survey people were told: “conservation benefits also come from well practised grouse moor management, because it retains heather moorland and some of the birds that depend on this habitat.” Such conservation benefits are not mentioned in the first survey.

- In the section on “The Future of Grouse Moorlands in the Scottish Uplands and Hen Harriers” in the second survey information was provided about how organisations involved in shooting and conservation are trying to find a solution to the conflict that allow managed grouse moors and conservation of hen harriers. This is not mentioned in the first survey.

- A differences in emphasis in how the information is provided, which may evoke a different sense of the importance of the Scottish uplands. In the section about the uplands of Scotland they are described in survey 2 as "the purple moors of the Scottish uplands" instead of just the "uplands" as in survey 1. The use of the phrases “an important part of our cultural heritage” and "internationally important species of animals and plants" in describing the Scottish uplands in survey 2 paint a different picture of the Scottish uplands than the description in survey 1 does.

- In the box on red grouse in the second survey it is stated that “grouse shooting contributed approximately £23 million to the rural economy each year and supported over 1,000 jobs” while in the first survey the figures given are £5 million and 1,240 jobs.

2. Hen harriers were depicted as less threatened in Information pack 2:

- Less information on hen harrier persecution is provided;

- More information on how moorland management assists hen harriers is given, for example that hen harriers benefit from the control of foxes for grouse shooting;

- A sentence about suitable habitat on which hen harriers are absent “There are large areas of suitable habitat where hen harriers are currently absent, and these are predominantly areas where grouse management is most intensive”. This is not explicitly stated in the first survey.

3. Golden eagles are depicted in less detail and in a less “sympathetic” way in the second information pack:

- In the second survey it is stated that golden eagles feed on birds including grouse; this was not stated in the first survey.

- In the first survey more information is given on golden eagles, such as how they mate for life, how population numbers have recovered during the 20th century, and how illegal persecution is carried out. All of this information is absent in the second survey.

A priori, the expected effects of the second information pack on stated preferences might be summarized as lower levels of willingness to pay for both hen harriers and golden eagles, and greater willingness to choose a management option rather than the status quo in order to improve prospects for conflict resolution in study 2 as compared to study 1. We can now test these impacts econometrically.

5. Results

In the first survey, we obtained 233 responses from 1,000 mail outs, a 23% response rate. In the second survey, we obtained 347 responses from 1,700 mail outs, a 20% response rate. The observations from two studies were combined and modelled using the approach outlined in section 3. The results of the G-MNL model with estimated parameters for dataset-specific covariates of scale (θ) and its variance (λ) are presented in Table 1 (see equation (8) for details). The variables of the model include alternative specific constants associated with different protection programs (LAW , $FEED$, $MOVE$), dummy-coded levels of improvement of hen harriers (HH_1, HH_2) and golden eagles (GE_1, GE_2), and the continuously coded cost (FEE). All preference parameters were assumed to be normally distributed. We allowed all parameters to be study-specific (superscripts on variable names indicate the two different samples), except for cost (FEE), which was constrained to be equal in both studies for identification purposes. The model allows for correlations between all random parameters associated with each study.[6] The estimation was performed in MatLab using 1000 shuffled Halton draws. Since the log-likelihood function in the case of G-MNL is not necessarily convex, we used multiple starting points to ensure convergence at the global maximum. Standard errors of coefficients associated with standard deviations of random parameters were simulated using Krinsky and Robb method (Krinsky et al., 1986).

We start the analysis by noting that the model displays a very good fit, as indicated by Akaike information criterion (AIC) and McFadden's pseudo R^2. All parameters are highly significant and of expected sign. Statistical significance of coefficients associated with standard deviations of normally distributed parameters indicates that there is substantial un-observed preference heterogeneity with respect to all model parameters. The alternative specific constants associated with each protection program (LAW , $FEED$, $MOVE$) were relatively high. This illustrates the importance of including not only the end results of a proposed scenario but also the means of achieving it (Czajkowski et al., 2009). Coefficients associated with improvements in hen harriers (HH) and golden eagle (GE) populations indicate that overall respondents were more concerned with the latter, but in both cases displayed only limited sensitivity to the scale of improvement. In addition, the respondents in the second sample revealed a higher degree of preference heterogeneity with respect to protecting these bird species, as indicated by higher estimates of standard deviations associated with these parameters in study 2 in comparison with study 1. Comparing the relative importance of different attribute levels is not straightforward, however, since we allowed for correlations between the attributes. Since the random parameter associated with an attribute could be positively or negatively correlated with the cost, the implicit prices associated with these attributes do not necessarily reflect coefficients for the means associated with each attribute. We investigate this further below when simulated implicit prices of the attribute levels in both studies are presented.

[6] This means that we constrained some elements of the Cholesky matrix to equal 0, to rule out correlations between variables associated with different studies. For example, it would make no sense for HH_1^1 (partial improvement of hen harriers in study 1) to be correlated with HH_1^2 (analogous attribute for study 2), as these attributes never appeared together.

We found that in estimation the value of γ^* consistently approached negative infinity, what is equivalent of γ approaching 0. For this reason, and to avoid numerical problems, we constrained the γ parameter to 0. As a result, in our model residual taste heterogeneity was scaled in the same way as means of the distributions. The high and statistically significant value of τ indicates the presence of high unobserved scale heterogeneity – respondents in the two studies were different from one another in terms of how deterministic or how random their choices were. In addition, we found that introducing a dataset-specific dummy variable as a covariate of scale and its variance (parameters θ and λ, respectively) revealed significant differences between the two studies in terms of how deterministic respondents' choices were (effective scale was higher in the first study), as well as how differentiated the respondents were in terms of their scale (scale variance was lower in the second study). This illustrates that when unobserved scale heterogeneity is allowed for, controlling for both scale and its variance differences between datasets may yield considerable insights. In our case, these differences in scale relate to changes in information provided to respondents.

In addition to the model presented in Table 1, we tried other specifications in which selected parameters within- and between- studies were constrained to be equal. Since in our approach all model parameters were estimated jointly, and differences in scale (and its variance) were controlled, it is possible to use standard statistical tests (such as a likelihood ratio test) to formally test for the equality of model parameters between-studies. In our case, the results of these tests indicated that respective utility function parameters were indeed statistically different between two studies.[7]

Finally, in order to compare respondents' preferences between two studies in terms of monetary values associated with each attribute level, we calculated implicit prices. Since all parameters in our model (including cost) were normally distributed, the resulting ratio distribution of WTP has infinite moments (i.e. does not have well defined mean and standard deviation; Fieller, 1932; Meijer et al., 2006; Daly et al., forthcoming). Instead we employed the following procedure to simulate the median of each distribution of WTP:

1. We took $n = 1000$ draws from multivariate normal distribution described by a vector of estimated parameters and the asymptotic variance-covariance matrix;
2. For each of n draws we decomposed the resulting vector of parameters to a vector of means of random parameters associated with 15 choice attributes $(\mathbf{B})$, and the accompanying Cholesky matrix, composed of the remaining elements of the vector drawn in 1. The Cholesky matrix was then multiplied by its inversion, resulting in the variance-covariance matrix $\mathbf{VAR}$ associated with $\mathbf{B}$;
3. For each of the n draws we took $m = 10000$ draws from multivariate normal distribution described by $\mathbf{B}$ and $\mathbf{VAR}$;

[7] Even though means of some parameters may appear similar, their standard deviations and correlations with other parameters may be quite different, resulting in rejecting the equality hypothesis. This is also illustrated with implicit prices associated with some parameters which may have similar means, but apparently quite different correlation coefficients with the price (FEE).

4. For each of the $n \cdot m$ draws we calculated implicit prices of the attribute levels, and calculated their medians.

The results are presented in Table 2. We note that respondents of study 2 had substantially higher WTPs for alternative specific constants associated with different protection methods. Within each study, however, they were relatively close. The respondents of study 2 were willing to pay less for the protection of hen harriers, and a more for the protection of golden eagles than the respondents of the first study. Overall, these results illustrate how changes in the information provided may lead to changes in estimated implicit prices.

6. Conclusions

Stated preference researchers have been interested for many years in the effects of information provided to respondents on their stated values. In this paper, we used a stakeholder group to devise an alternative presentation of information on an important biodiversity conservation issue – the management of raptors on moorland in the UK – to a presentation arrived at by the authors based on the scientific literature. Neither information set could be described as more correct, but rather both reflect differences in interpretation and emphasis which are common in arguments over conservation management. We then developed a method of econometrically modelling responses which allowed for heterogeneity in preferences across and within information treatments, as well as variations in relative scale within and between treatments. This showed that the random element of choice varied across the two samples, whilst the degree to which respondents within each treatment vary in terms of the random component of utility also differs. We also find considerable evidence of preference variation in the deterministic component of choices, and small differences in willingness to pay.

Overall, what emerges is a richer way of representing the effects of changing information on preferences and choice. In this paper, the emphasis was on different descriptions of the good. However, the method could equally be applied to differences in framing, different ways of presenting information (eg verbal versus visual), and different ways of collecting responses (eg internet versus in-person). Our results show that the early fascination with the effects of information simply in terms of mean Willingness to Pay misses a large part of the picture.

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Figure One – example choice card

	DO NOTHING Maintain current management.	LAW Stricter law enforcement.	FEED Feeding stations away from grouse.	MOVE Move eggs and chicks to new sites.
HEN HARRIER	20% population decline.	Maintain current population.	Maintain current population.	Maintain current population.
GOLDEN EAGLE	20% population decline.	20% population increase.	Maintain current population.	20% population decline.
COST	£0	£50	£50	£10
YOUR CHOICE (please tick one only)	ꞥ	ꞥ	ꞥ	ꞥ

Table 1. The results of the G-MNL model

Variable	Mean			Standard deviation		
	coeff.	s.e.	p-value	coeff.	s.e.	p-value
LAW^1	12.0039	3.7172	0.0012	14.4188	4.3896	0.0010
$FEED^1$	11.9657	3.7546	0.0014	14.1252	4.2400	0.0009
$MOVE^1$	11.7394	3.7047	0.0015	14.2955	4.2929	0.0009
HH_1^1	4.0516	0.9756	0.0000	4.5890	1.1379	0.0001
HH_2^1	4.5623	1.0186	0.0000	4.9217	1.2019	0.0000
GE_1^1	5.0887	1.0913	0.0000	4.0150	0.9782	0.0000
GE_2^1	6.1589	1.2774	0.0000	4.7439	1.2482	0.0001
LAW^2	11.0462	2.3578	0.0000	10.8648	2.1273	0.0000
$FEED^2$	11.5625	2.3680	0.0000	11.8904	2.1758	0.0000
$MOVE^2$	10.3751	2.4152	0.0000	11.6050	2.0596	0.0000
HH_1^2	3.0370	0.7846	0.0001	7.6760	1.4002	0.0000
HH_2^2	3.5371	0.7355	0.0000	7.2888	1.3270	0.0000
GE_1^2	5.3024	1.0273	0.0000	8.1872	1.5464	0.0000
GE_2^2	6.1771	1.1045	0.0000	8.1992	1.4667	0.0000
FEE	-8.8614	1.9715	0.0000	14.1493	2.4345	0.0000
Elements of the lower triangular of Cholesky matrix are skipped						
θ	0.7137	0.2614	0.0063	–	–	–
λ	-0.2621	0.0496	0.0000	–	–	–
τ	7.2059	1.1175	0.0000	–	–	–
γ	0	fixed	–	–	–	–
Log-likelihood	-2736.2711					
McFadden's pseudo R^2	0.4279					
AIC/*n*	5750.5423					
n (observations)	3450					
k (parameters)	90					

Table 2. Simulated median implicit prices of the attribute levels (GB Pounds per household per year)

Parameter	Implicit price (GBP)	
	Study 1	Study 2
LAW	25.44	52.25
FEED	24.19	58.43
MOVE	22.51	54.68
HH_1	20.02	18.62
HH_2	20.93	19.11
GE_1	26.19	29.92
GE_2	28.37	33.35