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The Effects of Experience on Preference Uncertainty: Theory and Empirics for Public and Quasi-Public Goods

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Abstract: This paper develops a model of demand estimation in which consumers learn about their true preferences through consumption experiences. We develop a theoretical model of Bayesian updating, perform comparative statics over the model, and show how the theoretical model can be consistently incorporated into a reduced form econometric model. We then estimate the model using data collected for two quasi-public goods. We find that the predictions of the theoretical exercise that additional experience with a good will make consumers more certain over their preferences in both mean and variance are supported in each case.

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1. Introduction

Consumers often make decisions under uncertainty about their preferences, such as when a firm introduces a new product. Experience goods are goods for which consumers do not know their preferences with certainty, where information about their preference is learned with each consumption event (Nelson, 1970; 1974; Stigler et al., 1977). Consumers are usually modeled as having a true preference parameter, or type, which they learn about through Bayesian updating (Ackerberg, 2003). Beliefs regarding their true preference for an experience good are then revealed in their purchasing decisions.

There is significant interest in empirically identifying how learning about goods affects consumer demand (Erdem et al., 1996; Ackerberg, 2003; Osborne, 2011). Identifying how learning affects preferences, and subsequently demand elasticities, is important for firms' pricing decisions in order to efficiently price in an experience goods market (Crawford et al., 2005; Goeree, 2008). In this literature, a formal model of learning and information agglomeration is often integrated into the demand framework in a theoretically consistent way (Ackerberg, 2003; Israel, 2005). It is somewhat surprising, then, that learning and experience have not been taken into account in a theoretically consistent way in demand estimation for public or quasi-public goods such as outdoor recreation demand or environmental amenities, given the nature of demand estimation procedures for such goods and that experience has been shown to matter for preference uncertainty these contexts (Boyle et. al. 1993; Whitehead et al., 1995; Cameron et al., 1997; Hanley et al., 2009).

Demand estimation for public or quasi-public goods often involves non-market valuation because markets for such goods are incomplete (Carson et al., forthcoming). For example, it is difficult to value the establishment of a new national park or a biodiversity conservation program with market data. As a result, demand estimation for public and quasi-public goods makes use of a range of non-market valuation methods. In situations where non-use values are likely to be important, stated preference methods with discrete choice experiment elicitation format are often used. Choice experiments involve eliciting consumers' willingness to pay for a particular environmental amenity after sometimes lengthy descriptions of the potential uses, benefits and costs of the good being evaluated. Discrete choice experiments, then, are a natural setting where previous experience with a public good such as river water quality or wilderness land can interact with information provided by the researcher in the course of a stated preference exercise to affect consumer's willingness to pay.

This paper investigates the theoretical and empirical implications of explicitly accounting for prior experience with an environmental good insofar as it can affect consumers' preferences. Assuming a Bayesian updating rule, we show explicitly how prior distributions over utility from a good will be updated with additional information in the form of experience to influence posterior distributions over utility. We then apply a generalized random coefficients multinomial logit model (G-MNL) which captures the salient features of the theoretical exercise. We estimate this model using two different data sets.

We find that experience, as shown in the theoretical exercise, decreases the variance of utility function error term, but also the variation of this variance when it is allowed to differ between respondents. Further, we find that the information set (e.g., the signal) given to respondents significantly changes both the variance of utility function error term, but also the variation of this variance. Both of these results suggest that respondents update their preferences as a function of consumption experiences and information provided during stated preference surveys in a way consistent with Bayesian updating. Our paper thus offers a theoretically consistent and parsimonious empirical technique for taking experience-driven and information driven preference changes into account for future researchers using random utility based valuation approaches.

The remainder of this paper is organized as follows: Section 2 develops a simple theoretical model which shows how information can affect the distribution of valuations for experience goods. Section 3 develops a generalized random coefficients logit model and discusses its properties with respect to the theoretical exercise in Section 2. Section 4 introduces and explains the empirical studies which we evaluate. Section 5 presents results and Section 6 offers discussion.

2. Theoretical Motivation

This section shows in a simple Bayesian framework the effects of experience on the observed choices of consumers when experience helps to refine consumption choices. We demonstrate how this framework can be carried over to the case of public and quasi-public goods within the standard random utility model of demand (McFadden, 1974; Hanemann, 1984). Ignoring previous experience will make consumer choices appear more random than they actually are along two dimensions. First, previous experience will decrease the average magnitude of the idiosyncratic component of choices. Second, previous experience will decrease the variance of this idiosyncratic component. Put another way, Bayesian updating predicts that previous experience will increase the scale and decrease the scale variance heterogeneity for individual consumers.

In line with the standard random utility model, assume the utility derived from a good is:

$$U_{ijt} = \boldsymbol{\beta}_j' \mathbf{X}_j + \delta_{ij} + \varepsilon_{ijt} \tag{1}$$

where i indexes an individual, j a good, and t time. The traits of good *j* are given by the vector $\mathbf{X}_j$ and marginal utility over those traits of good j are $\boldsymbol{\beta}_j$; for exposition here, they are not assumed to be individual specific as with a random coefficients model but could be represented in that way with no loss.[4] The idiosyncratic utility component is assumed normal and iid: $\varepsilon_{ijt} \sim N\left(0,\sigma_{\varepsilon}^{2}\right)$. Assume further that there is an individual/product fixed effect that can be thought off as an individual's type, δ_{ij}. Each individual's type is itself a realization of a random variable subject to a time invariant distribution $\delta_{ij} \sim N\left(0,\sigma_{j}^{2}\right)$. We assume the variance of consumers' true type utility is constant across the population but that assumption can be relaxed at no qualitative cost.

The consumers' learning problem can be thought of as learning about the "true" properties of their type, δ_{ij}, and thereby leading to changes in the distribution of consumers' utility function taste parameters.[5] Individuals never receive a signal that perfectly reveals their type in this model. Instead individuals observe the sum of their time invariant type, $\delta_{ij}^{t} = \delta_{ij} + \varepsilon_{ijt}$. As a result, individuals must infer what their true type is by evaluating the likelihood they had the experience they did given their priors over type and the distribution of the idiosyncratic error term.[6]

Following DeGroot (2004) and Ackerberg (2003), assuming priors over a consumer's type, δ_{ij}, are normal, $\delta_{ij}^{0} \sim N\left(0,\sigma_{o}^{2}\right)$, after K consumption experiences with the good, posterior beliefs about type can be represented as:

[4] We relax this assumption below and consider the implications of more general utility specifications in Appendix A.

[5] Note that learning could affect both means and variances of random taste parameters, and as a result, the mean and variance of willingness to pay. This will be discussed in more detail below.

[6] For example, when a new good is introduced, say a new restaurant, a consumer will not likely be able to distinguish between the possibility they like that restaurant more than the average patron (e.g., their δ_{ij}) or if they happened to have a particularly good experience on that occasion (e.g., ε_{ijt}).

$$\delta_{it}^{k} \sim N\left(\frac{\sum_{t=1}^{K}\delta_{ij}^{t}}{\frac{\sigma_{\varepsilon}^{2}}{\sigma_{o}^{2}}+K}, \frac{\sigma_{\delta}^{2}}{\frac{\sigma_{\varepsilon}^{2}}{\sigma_{o}^{2}}+K}\right) \qquad (2)$$

Note that if an individual consumes product *j* in each period, then $K = t$. By inspection, additional experience has an ambiguous effect on the mean of beliefs over type; the relative strength of an individual's experience must be compared to the reduction in mean from additional experiences. The variance of beliefs over type is falling in experience (e.g., the second term falls as K increases).

Now consider how this model of learning would manifest itself in the dynamics of consumption decisions. For exposition, assume an individual's true type is half of one standard deviation below the mean type: $\delta_{ij} = -.5\sigma_{\varepsilon}^{2}$, and that the variance of both the prior and true type is one. In this example, we plot the posterior given an expected draws (e.g., the posterior conditional on draws of the individual i's true type: $\delta_{ij}^{t} = \delta_{ij} + \varepsilon_{ijt} = -.5$). Put another way, we parameterize this example so that there is no noise introduced by the idiosyncratic term. Figure 1 shows the updating of the posterior distribution of beliefs over type, δ_{ij}^{K}, for one and two draws respectively.

There are two important features of Figure 1. First is that the consumer's posterior mean type, $E\left[\delta_{ij}^{K}\right]$, falls given new consumption experiences because each signal is below the mean of their prior. Second, the variance around the posterior mean is decreasing as successive signals mechanically decrease the variance of posterior beliefs. In this simple example, we assume that both consumption signals are the mean true signal for expositional purposes, but this assumption can be relaxed without qualitative loss.[7] Figure 1 and equation 2 above both show that a model of Bayesian learning dictates that additional

[7] One could perform Monte Carlo simulations over the entire distribution not conditioning on realized signals. There would be no qualitative differences, though, as it would have the effect of increasing the size of the tails in each posterior distribution.

consumption experiences with a good will decrease the variance of a consumer's utility for that good. Alternatively, one can model uncertainty over an individual's type and the idiosyncratic error term as forming a composite error term. With this approach, the variance of the composite error term should be allowed to decrease as experience levels with a good increase. Effectively, the magnitude of the composite idiosyncratic component of utility decreases relative to the deterministic component as experience with the good increases.

Now consider the implications of updating behavior for a multiple-good or multiple-attribute discrete choice model in a random utility framework (McFadden, 1974). Once again, the utility associated with any choice alternative 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. Specifically consider the following empirical specification of a random parameters multinomial choice model:

$$U_{it}\left(Alternative = j\right) = U_{ijt} = \boldsymbol{\beta}_i'\mathbf{x}_{ijt} + \varepsilon_{ijt}/\sigma_i \;, \tag{3}$$

where:

- U_{ijt} represents respondent i's utility associated with selecting alternative j out of a set of J available alternatives at time occasion t;
- the stochastic component of the utility function (ε) may be interpreted as resulting from researcher's inability to observe all attributes of choice and all significant characteristics of respondents (McFadden, 1976), or as decision maker's choice from a set of his decision rules (Manski, 1977). Pragmatically, introducing the error term is equivalent of assuming that utility levels are random variables, as it is otherwise impossible to explain why apparently equal individuals (equal in all attributes which can be observed) may choose different options;

- $\mathbf{x}_{ijt}$ is a vector of respondent- and alternative-specific choice attributes, i.e. goods or their characteristics;
- $\boldsymbol{\beta}_i$ represents a vector of individual-specific taste parameters associated with marginal utilities of the choice attributes. Denoting the multivariate distribution of these parameters in the sample as $\mathbf{f}$, $\boldsymbol{\beta}_i \sim \mathbf{f}(\mathbf{b},\boldsymbol{\Sigma})$, where $\mathbf{b}$ is a vector of sample means and $\boldsymbol{\Sigma}$ is a variance-covariance matrix, with a vector of square roots of diagonal elements $\mathbf{s}$ which represent standard deviations of random taste parameters;
- σ_i is the scale parameter which allows one to introduce the desired level of randomness to respondents' choices.[8] The scale parameter can indeed be allowed to be individual-specific, as it is reasonable to allow different agents in an economy to have relatively larger or smaller idiosyncratic components as opposed to deterministic components of the utility function.[9] The scale heterogeneity of the agents can be described with the parameter τ, such that given the scale distribution g, $\sigma_i \sim g(1,\tau)$.[10]

The above specification of the random utility model accounts for unobserved preference heterogeneity in terms of both taste parameters and scale. In addition, one can introduce observed preference heterogeneity in the model by including individual-specific covariates of means of random taste parameters $\mathbf{b}$, their variances , the scale parameter σ or its variance τ. A convenient reduced form

[8] Note, that the scale cannot be econometrically separated from the other parameters of the utility function and the estimates of taste parameters are in fact multiplications of the underlying taste parameters and scale (Fiebig et al., 2010). With no loss of generality one can normalize scale to 1 and, due of the ordinal nature of various utility functions, treat the estimates of utility function taste parameters as true taste parameters, which can only be interpreted in relation to each other.

[9] For example, when one agent has very well-defined preferences, one would expect their deterministic component of utility to be large in magnitude relative to the idiosyncratic component.

[10] In this case the mean of the scale parameter is normalized to 1.

way of accounting for previous experience is by estimating the term σ explicitly as a function of prior experience, **z**, so that $\sigma_i \sim g\left(1+\boldsymbol{\phi}'\mathbf{z}_i,\tau\right)$. Note that this is equivalent to experience influencing all the taste parameters in the same way. Provided that all utility function taste parameters are random and they are allowed to be correlated, this effect may already be to some extent accounted for by off-diagonal elements of $\boldsymbol{\Sigma}$ (Hess et al., forthcoming). Collecting the common effect for all taste parameters has, however, a very interesting behavioral interpretation – allowing scale to be a function of previous experience permits the magnitude of the error term, ε_{ij}, to be systematically related to experience. As a result, the relative importance of observable characteristics in determining utility is exactly what is implied by Figure 1 above: as experience increases, agents learn their type with more certainty so that the relative importance of observable characteristics of the good and the consumer become relatively more important (i.e. choices become less random).[11]

Finally, just as experience-related covariates in the mean scale collect common effects for all taste parameters, introducing experience-related covariates in the variance of the scale parameter collects common effects for variances of all random parameters. In this case, the scale variance can be modeled as a function of experience, $\sigma_i \sim g\left(1,\tau\exp\left(\boldsymbol{\xi}'\mathbf{z}_i\right)\right)$. Behaviorally, this effect allows experience to cause respondents to become more similar/different with respect to how deterministic their choices are.

This paper proposes a way in which experience can be accounted for in econometric modeling of consumers' preferences in a random utility framework as introduced above. In particular, by focusing on effects of experience on scale and scale variance, which collect common effects for all means and variances of random taste parameters as explained in the preceding paragraph, we allow for Bayesian updating to inform the econometric specification. We demonstrate how this can influence preferences

[11] Another way to interpret this is that the errors in the random utility model are heteroskedastic in previous experience.

and, as a result, willingness to pay estimates.[12] The method developed in this paper is widely applicable to both stated and revealed preference data.

3. Econometric treatment

In this section we set out a method for accounting for the effects of experience on consumers' preferences in discrete choice models, by allowing for experience-related observable and unobservable preference and scale heterogeneity in a manner consistent with the theoretical treatment of the preceding section. We later apply these methods using two case study data sets to investigate how experience and familiarity with the good influences respondents' preferences and scale.

The random utility framework presented in the previous section conveniently lends itself to econometric modeling – random utility theory is transformed into different econometric models by making assumptions about the distribution of the random error term and the random parameters. Typically, ε_{ij} is assumed to be independently and identically (iid) Extreme Value Type 1 distributed across individuals and alternatives; in addition, assuming that all the random taste parameters are multivariate normally distributed[13] and that the individual scale parameter is log-normally distributed[14] leads to the

[12] There are other ways in which experience has been introduced in demand estimation studies and we briefly review them in Appendix A. This model, though, is can be integrated with those alternative techniques as well, but the technique we develop here is similar to those discussed in Appendix A if consumers, on average, have unbiased priors.

[13] $\boldsymbol{\beta}_i \sim MVN(\mathbf{b},\boldsymbol{\Sigma})$, so $\boldsymbol{\beta}_i = \mathbf{b} + \boldsymbol{\Gamma\Omega\varsigma}_i$, where $\boldsymbol{\Gamma\Omega}$ is a lower triangular matrix resulting from Cholesky decomposition of the variance-covariance matrix $\boldsymbol{\Sigma}$ of random taste parameters ($\boldsymbol{\Sigma} = \boldsymbol{\Gamma\Omega}(\boldsymbol{\Gamma\Omega})'$ with the vector of square roots of diagonal elements $\mathbf{s}$), such that $\boldsymbol{\Gamma}$ has ones on the diagonal and possibly non-zero below diagonal elements accounting for correlations of random taste parameters, $\boldsymbol{\Omega}$ is a diagonal matrix of standard deviations $\mathbf{s}$

Generalized Multinomial Random Parameters Logit model type II (G-MNL; Fiebig et al., 2010). Following the notation introduced in section II, respondent i's utility associated with choosing alternative j is:

$$U_{ijt} = \left(\sigma_i\left(\mathbf{b}+\boldsymbol{\upsilon}_i\right)\right)' \mathbf{x}_{ijt} + \varepsilon_{ijt} \ , \tag{4}$$

where the individual-specific random taste parameters are now represented by a vector of their population means $\mathbf{b}$ and individual-specific deviations from these means $\boldsymbol{\upsilon}_i$. The new subscript t represents different choice tasks the same respondent may face – in discrete choice experiments an individual is usually confronted with numerous choice tasks which allows the researcher to extract more information from each respondent of the study, and facilitates identification of preference and scale heterogeneity (Ruud, 1996; Revelt et al., 1998; Fosgerau, 2006; Hess et al., 2011).

The key focus of our theoretical treatment is on the representation of the effects of familiarity in a random utility model. Therefore, in order to empirically investigate these possible relationships between respondents' familiarity with the goods and the taste parameters and scale in their utility functions, we adapt the G-MNL model to account for the effects of experience, as explained in section II. This can be done by introducing indicators of experience or familiarity with the good $\left(\mathbf{z}\right)$ as covariates or means and variances of random taste parameters $\boldsymbol{\beta}_i \sim MVN\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i, \boldsymbol{\Sigma}\exp\left(\boldsymbol{\psi}'\mathbf{z}_i\right)\right)$ and/or as covariates of random scale and its variance $\sigma_i \sim LN\left(1+\boldsymbol{\phi}'\mathbf{z}_i, \tau+\boldsymbol{\xi}'\mathbf{z}_i\right)$.[15]

, and $\boldsymbol{\varsigma}_i$ is a vector of random, normally distributed unobserved taste variations associated with taste parameters (with mean vector 0 and covariance (identity) matrix $\mathbf{I}$).

[14] $\sigma_i \sim LN\left(1,\tau\right)$, so $\sigma_i = \exp\left(\bar{\sigma}+\tau\varepsilon_{0i}\right)$ where $\varepsilon_{0i} \sim N\left(0,1\right)$ and $\bar{\sigma} = -\tau^2/2$.

[15] Since experience-related covariates enter diagonal elements of $\boldsymbol{\Sigma}$ only (i.e. only the variances of random taste parameters), $\boldsymbol{\Omega} = diag\left(\mathbf{s}\right)\exp\left(\boldsymbol{\psi}'\mathbf{z}_i\right)$.

The resulting model is flexible enough to capture observed and unobserved preference heterogeneity, as well as observed and unobserved scale heterogeneity. Importantly, allowing for scale heterogeneity provides a convenient way in which the behavior of the error term can be a function of previous experience which Section II shows must be allowed for in order for the empirical model to be consistent when allowing for Bayesian learning.

The above model specification results in the following probability of observing respondent i choosing alternative j out of the J available alternatives at choice occasion t :

$$
\begin{aligned}
&\Pr\left(y_{it}=j\right)=\frac{\exp\left(\exp\left(\sigma_i\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i+\boldsymbol{\upsilon}_i\right)\right)'\mathbf{x}_{ijt}\right)}{\sum_{k=1}^{J_{it}}\exp\left(\left(\sigma_i\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i+\boldsymbol{\upsilon}_i\right)\right)'\mathbf{x}_{ikt}\right)}\\
&\text{where:}\\
&\sigma_i=\bar{\sigma}+\boldsymbol{\phi}'\mathbf{z}_i+\tau\exp\left(\boldsymbol{\xi}'\mathbf{z}_i\right)\varepsilon_{0i} \qquad .\\
&\boldsymbol{\upsilon}_i=\boldsymbol{\Gamma\Omega\varsigma}_i\\
&\boldsymbol{\Omega}=diag\left(\mathbf{s}\right)\exp\left(\boldsymbol{\psi}'\mathbf{z}_i\right)
\end{aligned}
\tag{5}
$$

Since the probability is conditional on the random terms, the unconditional probability is obtained by multiple integration, the expression for which does not exist in closed form. Instead, it can be simulated by averaging over D draws from the assumed distributions (Revelt et al., 1998). As a result, the simulated log-likelihood function becomes:

$$
\log L=\sum_{i=i}^{I}\log\frac{1}{D}\sum_{d=1}^{D}\prod_{t=1}^{T_i}\frac{\exp\left(\left[\sigma_{id}\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i+\boldsymbol{\upsilon}_{id}\right)\right]'\mathbf{x}_{ijt}\right)}{\sum_{k=1}^{J_{it}}\exp\left(\left[\sigma_{id}\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i+\boldsymbol{\upsilon}_{id}\right)\right]'\mathbf{x}_{ikt}\right)}\ . \tag{6}
$$

In the Results section of this paper we estimate the above empirical model for two different stated preference choice experiments. Because of the importance of information processing in motivating our approach, we are particularly interested in the coefficients on $\mathbf{z}$, which will be proxies for prior experience with the good being studied, and which enter the utility function as covariates of the scale parameter and its variance, thus allowing for Bayesian updating.

4. Description of Data

In this paper, we make use of two different choice experiment data sets to explore the effects of respondent familiarity with two different environmental goods, using the theoretical and econometric framework set out above. This section describes those two data sets. In the first dataset, two different information treatments were given to randomly selected respondents. This allows us to later test whether differing information can significantly affect scale and scale variance heterogeneity. The first data set also uses previous levels of experience with a good to explain scale and scale variance heterogeneity. The second dataset uses only previous experience levels with a good in order to explain scale and scale variance heterogeneity as information treatments do not vary across the survey sample.

4.1. Raptor conservation on heather moorland

Management of heather moorlands in the uplands of the UK for Red Grouse shooting has led to declines in several species of birds of prey (Newton, 1998), since the aim of grouse management is to maximize numbers of birds available for shooting in the autumn, and birds of prey are seen as threats to grouse numbers. Grouse moor management involves a mixture of vegetation management (e.g. heather burning) and predator control (Hudson et al., 1995). One particular conflict which has arisen in this context concerns the management of Hen Harriers (*Circus cyaneus*) on sporting estates. Hen Harriers are listed as endangered raptors (birds of prey) due to population declines in the last 200 years (Baillie et al., 2009). Economic costs to grouse moor owners arise because harriers prey on grouse, and arguments between the conservation lobby and the sporting estate community have become polarized over time (Redpath et al., 2004; Thirgood et al., 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). Another iconic raptor species, the Golden Eagle, is also found in heather moorlands. Golden Eagles have also been subject to illegal persecution, particularly on 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 stated preference Choice Experiment (Hanley et al., 2010).[16] The choice experiment design consisted of four attributes. These were:

- Changes in the population of Hen Harriers on heather moorlands in Scotland. The levels for this attribute 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 for this attribute 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

[16] This dataset has been used in the context of combining datasets with different scale in the context of new information (Czajkowski et. al. 2012). That study does not account for experience, does not explicitly model the theoretical implications of Bayesian updating to inform the reduced form econometric specification developed here, nor does it allow for the precise interpretation of the results so as to support Bayesian updating.

included as labeled 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, labeled 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. Cost levels were chosen based on the results of a pilot survey.

Figure 2 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 behavioral 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 et al., 2008). The parameters of this distribution were derived from a preliminary model estimated on data available from a pilot study.[17] The final design consisted of 8 questionnaire versions, each with 6 choice cards per respondent.

[17] 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. The samples differed only in the information provided to respondents, and each respondent received only one set of information. The first survey, reported in Hanley et al. (2010), used an information pack developed solely by the research team, based on existing research findings. The second survey used an information pack which was re-written by a group of stakeholders engaged in moorland ownership, management and grouse shooting. 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.

The public good being valued in this choice experiment is thus the condition of heather moorlands in the Scottish uplands in terms of (i) populations of Hen harriers and (ii) populations of Golden Eagles. Responses were obtained from a random selection of households in Scotland, using a series of mail shots. Households were contacted by letter (addressed from the University of Stirling), and a 3-stage Dillman procedure followed in terms of reminder letters and new copies of the survey instrument. We obtained 557 responses from 2,700 mail outs. Since the information provided to respondents varied across the two surveys, we include a dummy variable to control for these differences in estimation (*study)*. We used the reported number of visits to Scottish uplands in the last 12 months $(visit)$, as an indicator of respondents' familiarity with the good.

4.2. Preferences for water quality improvements in Northern Ireland.

This study considered the economic value of potential improvements to coastal water quality such as may result from implementation of changes to the European Union's Bathing Waters Directive in 2015 to people living in Northern Ireland. The focus is on potential benefits to recreational users of coastal waters, and how these vary according to the extent of exposure to risks. The focus of this Choice Experiment was on the valuation of changes in coastal water quality to those who use beaches in Ireland for recreation, principally "active" recreationalists such as surfers, swimmers and sea kayakers. This group of respondents is likely to be particularly affected by changes planned under revisions to the Bathing Waters Directive, since many of the water quality parameters which this directive focuses on are those linked to human health and the exposure of beach users to illness from contact with water-borne pathogens such as fecal coliforms. The current revisions to the Directive relate to greater restrictions upon the standards for bathing water: the current "good" standard becomes the future "mandatory standard", the current "excellent" standard becomes the future "good" standard and the future "excellent standard" is twice as strict as the current "excellent" standard.[18] The attributes chosen for the Choice Experiment describe three relevant aspects of coastal water quality: benthic health, human health risks, and beach debris. We now describe each in more detail.

[18] http://ec.europa.eu/environment/water/water-bathing/summary.html

Benthic Health

Measures taken as part of complying with the revised directive will impact upon the 'health of the seas' through improvements at the benthic level. However, the concept of benthic health is not likely to be understandable to most members of the public, and so was related here to probable outcomes on vertebrate populations (birds, fish and marine mammal species). Levels selected were:

- No Improvement to the current situation which will mean no changes to the numbers or chance of seeing fish, birds and mammals.
- A small improvement in Benthic Health which will mean that there will be more fish, birds and mammals. This will mean that endangered species will be less likely to disappear from the seas around Northern Ireland, although respondents were told that it is unlikely that they would see any more fish, birds or mammals on an average visit to the beach.
- A large improvement in Benthic Health which will mean that there will be many more fish, birds and mammals with "…an increased chance of you seeing them on your average visit to the beach."

Health Risks

Health risk was included as fecal coliform and fecal streptococci bacteria concentrations are expected to be reduced under the new directive standards. The levels of fecal coliforms under current and future were then related to the risk of a stomach upset of ear infection, based upon dose response relationships. Attribute levels selected were:

- 10% Risk - No Change to the current risk of a stomach upset or ear infection from bathing in the sea (current risk as assessed by the EU).

- 5% Risk – Good Water Quality achieved with a somewhat reduced risk of stomach upsets and ear infections although risks still exist in particular for vulnerable groups such as children.
- Very Little Risk - Excellent Water Quality achieved with a larger reduction in the risk of stomach upsets and ear infections.

Debris Management

In addition to the likely direct impacts of the upcoming changes to the bathing water directive it was identified that management would impact upon the amount of litter and other debris found on the beaches and coastal waters. This was related to the amount of debris (such as cans, bottles, cotton buds, plastic bags, sanitary products etc.) on the beach and in the water. Three levels were selected:

- No Change – current levels of debris will remain.
- Prevention – more filtration of storm water, more regular cleaning of filters and better policing of fly tipping.
- Collection and Prevention – debris collected from beaches more regularly in addition to filtration and policing.

Finally, in order to estimate measures of economic value of changes in the environmental attributes listed above, we needed to include a cost attribute in the design. We used the per visit cost to the individual of visiting a beach with a given set characteristics (the costs of travel to the site) as this cost attribute. Travel costs have been used before as the price attribute in several choice experiments relating environmental quality changes to recreational behavior (e.g., Hanley et al., 2002; Christie et al., 2007). Six levels of additional cost were selected: 0, £0.6, £1.6, £3, £6, and £9.

The design of the experiment was generated using efficient design principles. With three blocks, this meant that each individual responded to 8 choice cards. In each choice card, respondents were asked to choose the option they preferred from three choices. A sample choice card in included as Figure 3.Some 558 respondents were surveyed on-site at a range of beaches around the Northern Irish coast in autumn 2011. In this study, the indicator of respondents' familiarity with the good "coastal water quality" which we used was the reported number of days spent at the beach each year $(bdays)$.

It should be noted that in both studies, our measures of familiarity, namely number of visits to the uplands and the beach, are not exogenous. These are likely to be correlated with preferences for amenities associated with each public good. Indeed, finding an instrument for experience or familiarity can always be an issue in empirical work on experience goods. As a result this study cannot identify a causal link between experience and scale nor scale variance. We can, however, still construct and estimate a model which is theoretically consistent with Bayesian updating of preferences and test whether the theoretical predictions of the model are correct.

5. Results

We now turn to the analysis of data collected in the two empirical studies described in section IV. For each dataset we estimated the augmented G-MNL model described in section III, which allows us to account for possible effects of experience on respondents' preferences, assuming all taste parameters to be random, normally distributed, and possibly correlated. The indicators of respondents' experience or familiarity with the goods were included as covariates of scale and its variance. The estimation was performed in MatLab using 1000 shuffled Halton draws to simulate distributions of random parameters. Since the log-likelihood function described in section III 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 with 10^6 draws (Krinsky et al., 1986). The estimation results for the two studies are presented in Tables 1 and 2.

The attributes related to the choice variables of the raptor conservation model (Table 1) 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). The parameters were allowed 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.[19] As a result, the vector of the attributes was:

$$\mathbf{X} = \begin{array}{l} LAW^1, FEED^1, MOVE^1, HH_1^1, HH_2^1, GE_1^1, GE_2^1, \\ LAW^2, FEED^2, MOVE^2, HH_1^2, HH_2^2, GE_1^2, GE_2^2, FEE \end{array} . \tag{6}$$

The indicator of experience and familiarity with the analyzed goods which we decided to use in this study was $visit$ – the reported number of visits to Scottish uplands in the last 12 months (mean 12.29). In addition, a binary variable $study$ entering as a covariate of scale and its variance, which allows us to control for possible scale differences between the two jointly estimated samples.

In the case of the water quality study the following dummy coded choice attributes were used: SQ – an alternative specific constant associated with the no change alternative, improvements in benthic health

[19] The model allows for correlations between all random parameters within each study only. 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.

and population (BH_1 – small increase, BH_2 – large increase) with no improvement as a reference level, reductions of health risks (HR_1 – reduction to 5% risk, HR_2 – reduction to 'very little risk') with the current 10% risk as a reference level, and improvements in debris management (DM_1 – prevention, DM_2 – collection and prevention). In addition, the linearly coded variable FEE represented the additional cost of travelling to each beach. The resulting vector of choice-specific variables was:

$$\mathbf{X} = SQ, BH_1, BH_2, HR_1, HR_2, DM_1, DM_2, FEE \ . \tag{6}$$

We used $bdays$ – reported number of days spent at the beach each year (mean 74.89) as a proxy of respondents' experience or familiarity with coastal water quality.

In the model for the raptor conservation study all taste 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 unobserved preference heterogeneity with respect to all taste parameters. The alternative specific constants associated with each protection program (LAW, $FEED$, $MOVE$) are relatively high. Coefficients associated with improvements in hen harriers (HH) and golden eagle (GE) populations show that overall respondents were more concerned with the latter, but in both cases displayed only limited sensitivity to the scale of improvement. The high and statistically significant value of τ indicates the presence of high unobserved scale heterogeneity – respondents 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 $(study)$ as a covariate of scale (σ) and its variance (τ) proved to be an efficient way of controlling for the differences in scale and its variance between the two samples. Put another way, the information treatment significantly affects the average relative magnitude of the error component versus the deterministic component of utility for respondents (scale) in addition to significantly affecting the variation in the average relative magnitude of the error component versus the deterministic component of utility across respondents (scale variance).

Finally, we note that increases in the measure of experience used here, namely the number of visits to Scottish uplands in the last 12 months (*visit*), decreased respondents' scale parameters. This means that respondents who were more familiar with uplands made, statistically, more deterministic choices. At the same time, *visit* significantly decreased scale variance, indicating that the scale parameters of respondents who had more experience became more similar. Put another way, we find that additional experience decreases the average relative magnitude of the error component versus the deterministic component of utility for respondents (scale) and significantly decreases the variation in the average relative magnitude of the error component versus the deterministic component of utility for respondents (scale variance). Both of these results are consistent with the model of Bayesian updating developed in Section 2.

The taste parameters of the coastal water quality study are also very well-behaved, all highly significant and of expected sign. As in the case of the raptor conservation study, there is a considerable amount of unobserved preference (taste) heterogeneity. The results indicate that respondents perceived debris management as the most important, followed by the improvements in benthic health and health risks. We used the number of days a respondent spent at the beach in the past year (*bday*) as a measure of experience with the good. As in the other study, respondents who visited beaches more often had a significantly higher scale parameter (i.e. lower magnitude of the error component in their random utility function), and significantly lower scale variance. This mirrors the results from the first study and is again consistent with the model o Bayesian updating developed in Section 2.

6. Conclusions

It is surprising that the full implications of experience on preference uncertainty have not received more attention in the literature on the estimation of demand for public goods (like conservation programs) for which market data does not exist. The key theoretical result of this paper, that experience significantly decreases the variance of a respondent's random utility error term and the variance of that error term across respondents, is consistent with a model of Bayesian updating. This paper then develops a reduced form econometric model of demand estimation which is consistent with such a theoretical framework. The main empirical finding is that these theoretical predictions of the effects of more experience on the random component of utility and how this is distributed across respondents are supported by two data sets relating to two different environmental goods: a pure public good (biodiversity conservation in the case of the moorland raptor study) and a quasi-public good (coastal water quality and amenity).[20] This econometric model is also implementable with revealed preference data and, as shown in the Appendix A, can be integrated into models which preference parameters are allowed to be functions of previous experience levels as well.

There are several implications of the results in this paper. First is whether consumers do update as Bayesians or use some other updating procedure. This paper shows that we cannot reject a Bayesian model of updating. However, this does not imply that the Bayesian model is the correct one. Other models posited by the literature include behavioral models such as confirmatory bias and cognitive load (Rabin et al., 1999; Gabaix et al., 2006). Second, it is unclear exactly how the distribution of experience within the data can interact with the estimation of random utility parameters. Since all parameters of the utility function can only be interpreted relative to scale, this is a non-trivial point. Third, and potentially most important for stated preference work, the results indicate that the importance of prior

[20] We refer to coastal water quality and amenity as a quasi-public good since increased participation in beach recreation due to an improvement in water quality could reduce the utility of a trip to the beach due to crowding.

experience, the information presented to respondents, and the interaction of the two has been largely omitted in theoretically consistent empirical work. This is especially troubling given the nature of stated preference work: respondents are presented with a large amount of information and asked to think about it before stating their preferences for various policy outcomes. The interacting roles of experience and information provision are thus particularly important in this field.

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Figure 1: Updating of Beliefs of δ_{ij}^{k}. $\sigma_{o}^{2}, \sigma_{\delta}^{2} = 1$, $\delta_{ij}^{0} = 0$, $\delta_{ij1} = \delta_{ij2} = -0.5$

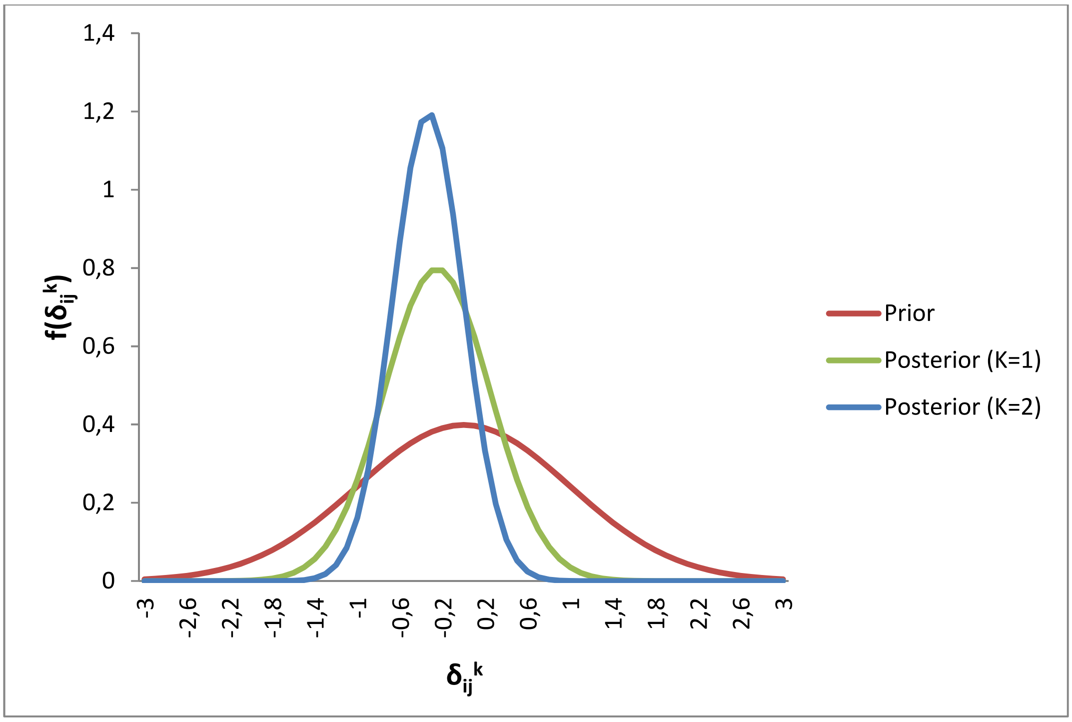

Figure 2. Example choice card from hen harrier survey

	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)	☐	☐	☐	☐

Figure 3. Example choice card from coastal water quality survey

	Beach A	**Beach B**	**Beach C**
Benthic Health and population.	**Small increase** More fish, mammals and birds. Limited potential to notice the change in species numbers.	**Large increase** More fish, mammals and birds and an increased potential of seeing these species.	**No Improvement**
Health Risk (of stomach upsets and ear infections)	**Very Little Risk** – excellent water quality	**5% Risk** – good water quality	**10% Risk** – no improvement
Debris Management	**Prevention** – more filtration of storm water, more regular cleaning of filters and better policing of fly tipping.	**Collection and Prevention** – debris collected from beaches more regularly in addition to filtration and policing.	**No Improvement**
Additional cost of travelling to each beach.	£3	£9	£0
Please tick the **<u>ONE</u>** option you prefer.	☐	☐	☐

Table 1. The discrete choice model results for the raptor conservation study

Variable	Mean			Standard deviation		
	coeff.	**s.e.**	**p-value**	**coeff.**	**s.e.**	**p-value**
LAW^1	7.8782	2.7071	0.0036	9.1263	3.1293	0.0035
$FEED^1$	7.6065	2.6606	0.0043	9.6311	3.2370	0.0029
$MOVE^1$	7.3762	2.6230	0.0049	9.6524	3.2031	0.0026
HH_1^1	2.7927	0.7073	0.0001	3.5527	0.9001	0.0001
HH_2^1	3.2469	0.7239	0.0000	3.7997	0.9346	0.0000
GE_1^1	3.5418	0.8565	0.0000	3.2436	0.7699	0.0000
GE_2^1	4.3103	0.9266	0.0000	3.8791	0.9252	0.0000
LAW^2	9.2704	1.6755	0.0000	9.0038	1.3753	0.0000
$FEED^2$	9.6932	1.6956	0.0000	10.0681	1.4723	0.0000
$MOVE^2$	8.6893	1.6712	0.0000	9.6371	1.4614	0.0000
HH_1^2	2.1162	0.5292	0.0001	5.6443	1.0100	0.0000
HH_2^2	2.5759	0.5241	0.0000	5.5244	0.9629	0.0000
GE_1^2	3.8493	0.7385	0.0000	6.2910	1.0631	0.0000
GE_2^2	4.6024	0.8178	0.0000	6.1752	1.0035	0.0000
FEE	-6.1964	1.3816	0.0000	10.5057	1.6377	0.0000
	Scale variance parameter (τ)					
	coeff.	**s.e.**	**p-value**			
τ	7.3734	0.8755	0.0000			
	Covariates of scale (σ)			**Covariates of scale variance (τ)**		
	coeff.	**s.e.**	**p-value**	**coeff.**	**s.e.**	**p-value**
$\log(visit)$	0.2796	0.0671	0.0000	-0.0641	0.0122	0.0000
$study$	0.5991	0.2753	0.0295	-0.2931	0.0565	0.0000
	Model characteristics					
Log-likelihood	-2732.4803					
McFadden’s pseudo R^2	0.4287					
AIC/n	1.2934					
n (observations)	3450					
k (parameters)	91					

Table 2. The discrete choice model results for the water quality study

Variable	Mean			Standard deviation		
	coeff.	s.e.	p-value	coeff.	s.e.	p-value
SQ	-1.9312	0.3182	0.0000	3.4674	0.4586	0.0000
BH_1	0.6446	0.1091	0.0000	0.5449	0.1589	0.0006
BH_2	0.9521	0.1538	0.0000	1.4242	0.2412	0.0000
HR_1	0.7179	0.1317	0.0000	1.1199	0.1905	0.0000
HR_2	0.9777	0.1564	0.0000	1.4468	0.2166	0.0000
DM_1	1.0348	0.1364	0.0000	1.2755	0.2248	0.0000
DM_2	1.2128	0.1327	0.0000	1.1100	0.2300	0.0000
FEE	-0.3145	0.0259	0.0000	0.3415	0.0325	0.0000
	Scale variance parameter (τ)					
	coeff.	**s.e.**	**p-value**			
τ	1.1164	0.3896	0.0042			
	Covariates of scale (σ)			**Covariates of scale variance (τ)**		
	coeff.	**s.e.**	**p-value**	**coeff.**	**s.e.**	**p-value**
$\log(bday)$	0.0778	0.0353	0.0274	-0.4807	0.2535	0.0579
	Model characteristics					
Log-likelihood	-3112.6638					
McFadden's pseudo R^2	0.3365					
AIC/*n*	1.4474					
n (observations)	4366					
k (parameters)	51					

Appendix A

This appendix considers alternative ways in which experience with a good (observed through a vector of indicators of the level of experience or familiarity with the good $\mathbf{z}$) may influence agent's preferences.

First, experience may cause individuals to change their preferences (taste) for the attributes of goods (e.g., Monroe, 1976; Araña et al., 2006). In our random utility specification this can be represented by introducing experience-related covariates in the means of random parameters, so that $\boldsymbol{\beta}_i \sim \mathbf{f}\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i,\boldsymbol{\Sigma}\right)$, were $\boldsymbol{\phi}$ is a new vector of parameters associated with attribute-specific effects of experience $\mathbf{z}$. Intuitively, gaining experience may cause individuals to (on average) prefer some choice attributes more or less than before.

Another way in which experience can influence individuals' preferences is through the variances of random taste parameters. This is equivalent to experienced individuals becoming more homogeneous or heterogeneous with respect to some attributes. Following the above specification this can be represented by including a vector of experience-related covariates $(\mathbf{z})$ in the variances of random parameters $(\mathbf{s})$ associated with attribute-specific taste parameters, so that $\boldsymbol{\beta}_i \sim \mathbf{f}\left(\mathbf{b},\boldsymbol{\Sigma}\exp\left(\boldsymbol{\psi}'\mathbf{z}_i\right)\right)$, where $\boldsymbol{\psi}$ is a diagonal matrix of parameters associated with experience-related covariates of the variances of random term parameters.

Note that all the ways in which experience can influence respondents' preferences (and hence choices) can influence the implied willingness to pay estimates. Through covariates of mean taste parameters, experience can influence the observed mean WTP in either way, depending on how does experience influence each attribute mean (including the monetary parameter in denominator of marginal rate of substitution). Similarly, through covariates of variances, experience may impact the variance of the empirical distribution of WTP. Finally, even though experience-related covariates of scale (or its variance) would not directly influence WTP, failing to account for statistically significant effects of experience may lead to biased estimates of utility function parameters, and as a result – biased estimates of WTP.