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Mikołaj Czajkowski

Nick Hanley

Jacob LaRiviere

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Mikołaj Czajkowski
Department of Economic Sciences, University of Warsaw, Poland, miq@wne.uw.edu.pl

Nick Hanley
Economics Division, University of Stirling, Scotland, n.d.hanley@stir.ac.uk

Jacob LaRiviere[1]
Department of Economics, University of Tennessee, jlarivi1@utk.edu

Abstract: This paper develop and estimates a model of demand estimation for environmental public goods which allows for consumers to learn about their 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 environmental goods. We find that the predictions of the theoretical exercise that additional experience makes consumers more certain over their preferences in both mean and variance are supported in each case.

Keywords: discrete choice experiment, preference learning, stated preferences, Bayesian updating, generalized multinomial logit, scale, scale variance.

JEL Codes: C51, D83, Q51, H43

[1] Corresponding author. 525 Stokely Management Center, Knoxville, TN 37996-0550. (865) 974-8114 jlarivi1@utk.edu

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 are uncertain about their preferences and learn about them with each consumption event (Nelson, 1970; 1974; Stigler et al., 1977). Economists often model experience goods by assuming consumers have a true preference parameter, or type, which they learn about through Bayesian updating. For private goods, preference uncertainty for an experience good is revealed in agents' purchasing decisions over time. However, for public goods or quasi-public goods, rich panel data to test and control for the relationship between experience and preference uncertainty or learning often do not exist because markets for public and quasi-public goods are often incomplete (Carson et al., forthcoming).

In the environmental economics literature, experience has been shown to matter for measures of preference uncertainty and as a determinant of willingness to pay (WTP) for public goods (Boyle et al., 1993; Adamowicz, 1994; Whitehead et al., 1995; Cameron et al., 1997; Breffle et al., 2000; Ferrini et al., 2007; Hanley et al., 2009). However, there is no broadly accepted way to test for and control for the effects of experience and learning on WTP, nor on preference uncertainty. This is particularly important for non-market valuation methods such as contingent valuation and discrete choice experiments (DCE) both because the public good being valued may be unfamiliar to many respondents and respondents are presented with information describing the public good at the beginning of the study. (Bateman et al., 2004; Carson et al., 2011).

This paper develops a theoretically consistent and readily implementable method of explicitly controlling for the effect of experience on preference uncertainty and willingness to pay estimates for public goods.[2] We develop a theoretical model which shows how additional experience affects preference uncertainty. This theoretical model is consistent with the notion of Bayesian learning, present in the literature (Ackerberg, 2003). We then link the theoretical model to a reduced form generalized mixed logit model (G-MNL) which captures the theoretical model's salient features. The extended G-MNL model both tests and controls for the effects of previous experience with the public good in estimating willingness to pay by allowing preferences to become more deterministic as experience with the good increases.[3] We then estimate the reduced form econometric model using two different data sets focusing on the effects of experience on preference uncertainty. In both datasets, increased experience with the public good increases preference certainty in the manner predicted by the theoretical exercise.

Our econometric model controls for the effect of experience on preference uncertainty by allowing the model's scale parameter to be a function of experience. The scale parameter weights the importance of the deterministic portion of a random utility model relative to the idiosyncratic portion. An increase in the scale parameter increases the relative importance of the deterministic portion of the utility function. Put another way, utility over a good, a public good or a quasi-public good becomes more deterministic as the scale parameter increases. We find that experience, consistent with the theoretical exercise, significantly increases the scale parameter. Also consistent with the theoretical exercise, we find that increases in experience also decrease the variance of the scale parameter across individuals. Both of these results suggest that respondents update their preferences for public goods as a function of

[2] There is significant interest in empirically identifying how learning about private goods affects preference uncertainty and consumer demand (Erdem et al., 1996; Ackerberg, 2003; Crawford et al., 2005; Goeree, 2008; Osborne, 2011). In this literature, a formal model of learning and information agglomeration is often integrated into the demand framework in a theoretically consistent way and estimation occurs in an explicitly Bayesian structural model (Ackerberg, 2003; Israel, 2005). Conversely, our model is a reduced form model with a specification that is informed by theory.

[3] Insofar as our model decomposes the error in a choice experiment setting, this work builds off of Scarpa et al. (2005).

consumption experiences. Importantly, we also find that accounting for experience affects the statistical significance of demand for certain aspects of public good provision.

There are several reasons why this paper is an important contribution. First, our model offers a theoretically consistent and parsimonious empirical technique for taking experience into account for future researchers using random utility based valuation approaches. While other researchers have accounted for experience in stated preference demand estimation, we are not aware of any commonly used approach which is theoretically motivated. Second, given that there are changes in willingness to pay estimates for public good attributes and the significance of those estimates when we control for experience, our paper suggests that controlling for the effects of experience can matter for policy evaluation. Lastly, the empirical model proposed is widely implementable for both private and public good settings, and for both revealed and stated preference data. While there are other simulation based structural models that can allow control for experience explicitly, the model here is easily applicable to a widely used method for estimating demand for public and quasi-public goods. As a result, we present a parsimonious way of controlling for the effect of experience on preference uncertainty.

2. Theoretical Motivation

In a simple Bayesian framework, this section shows the expected 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). This section shows 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:

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

where i indexes an individual, j a good, and t time. The traits or attributes 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 is drawn from the same distribution for all agents in the economy: $\varepsilon_{ijt} \sim N\left(0, \sigma_\varepsilon^2\right)$. Assume further that there is an individual fixed effect that can be thought off as an individual's type, δ_{ij}. Each individual's type is time invariant and itself a realization of a random variable from the distribution of potential types across the population: $\delta_{ij} \sim N\left(0, \sigma_j^2\right)$. We assume the variance of consumers' true type, δ_{ij}, 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}, leading to changes in the distribution of consumers' (perceived) 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 and idiosyncratic random utility component, $\delta_{ij}^t = \delta_{ij} + \varepsilon_{ijt}$. As a result, individuals must infer what their true type is (e.g., what there true preferences are) by evaluating the likelihood they had the experience they did given their priors over type and the distribution of the idiosyncratic error term.[6]

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[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}).

Following DeGroot (1970) 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:

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

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 distribution given an expected draw (e.g., the posterior conditional on draws of the individual i's true type: $\delta_{ij}^t = \delta_{ij} + \varepsilon_{ijt} = -.5$) in Figure 1. Put another way, we parameterize this example so that there is no noise introduced by the idiosyncratic term. Therefore, 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. The first is that, as expected, 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 show that a model of Bayesian learning dictates that additional consumption experiences with a good will decrease the variance of a consumer's utility for that good. Put another way, the variance of the composite error term decreases 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, and as uncertainty over a consumer's type is thus reduced. Therefore, the variance of the idiosyncratic portion of an agent's utility should be falling in the amount of experience with the good.

The above Bayesian model has implications not only for the magnitude of the deterministic component of utility relative to the idiosyncratic component of utility but also for the variance of that magnitude between respondents. Note that the variance of the full idiosyncratic portion of utility is, conditional on K consumption events is:

$$\operatorname{var}\left(\delta_{ij}+\varepsilon_{ijt}\middle|K\right)=\frac{\sigma_\delta^2+\sigma_\varepsilon^2}{\dfrac{\sigma_\delta^2+\sigma_\varepsilon^2}{\sigma_0^2}+K}+\sigma_\varepsilon^2. \tag{3}$$

By inspection, the variance of the uncertain portion of utility is also decreasing with experience.[8]

In sum, allowing for Bayesian learning through experience creates variation in the magnitude of the deterministic component of utility relative to the deterministic component of utility. The magnitude of the deterministic component of utility relative to the deterministic component of utility is often dictated

[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.
[8] Note that this result would hold even if the population error variance term were allowed to be heterogeneous across the population so long as it remains iid.

by the ‘scale’ parameter in empirical work. The theoretical model above shows that scale should increase as experience increases (e.g., the relative magnitude of the deterministic component of utility increases). Further, scale heterogeneity should decrease in experience as experience reduces the variance of the composite error term. From a theoretical perspective, not allowing the scale and scale variance to vary with experience amounts to misspecification of the error structure.

2.1 Application to the Random Utility Model Framework.

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:

$$U_{it}\left(Alternative = j\right) = U_{ijt} = \boldsymbol{\beta}_i' \mathbf{x}_{ijt} + \varepsilon_{ijt} / \sigma_i \ , \tag{4}$$

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).
- $\mathbf{x}_{ijt}$ 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. The multivariate distribution of these parameters in the sample is $\mathbf{f}$, $\boldsymbol{\beta}_i \sim \mathbf{f}(\mathbf{b},\boldsymbol{\Sigma})$, 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.[9] The scale parameter can 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.[10] The scale heterogeneity of the agents can be described with a parameter τ, such that given the scale distribution g, $\sigma_i \sim g(1,\tau)$.[11]

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 way of accounting for previous experience is by estimating the term σ explicitly as a function of prior experience, $\mathbf{z}$, so that $\sigma_i \sim g(1+\boldsymbol{\phi}'\mathbf{z}_i,\tau)$. Allowing the vector $\mathbf{z}$ to be comprised of experience related covariates, then, operationalizes the theoretical model presented above. Specifically, the theoretical

[9] 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.

[10] 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.

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

model predicts that experience related covariates should increase the mean of the scale parameter, thereby decreasing the magnitude of the error term in equation (4).

Allowing experience related covariates to affect the mean of the scale parameter is equivalent to allowing experience influencing all the magnitude of taste parameters. 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 $\mathbf{\Sigma}$ (Hess et al., 2012). 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 choices become less random.[12]

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.[13]

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

[13] Another alternative, adding experience as an explanatory variable for parameter uncertainty (e.g., in the covariance matrix of a parameter in a random coefficient model), has no clear theoretical foundation either. The goal of this modelling approach is to build a widely implementable model that accounts for experience in a theoretically motivated way without having the endogeneity concerns of prior work (e.g., Carson et al., 2009). This model is flexible enough to *control* for learning through experience without being subject to the same endogeneity concern as using experience directly as a linear argument in the random utility function. Another alternative is allowing experience to directly affect preference parameters using a large structural model (Goeree, 2008; Osborne, 2011). While theoretically consistent, these labor intensive models are not easily implementable by researchers in a public and quasi-public good setting.

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, we implement a reduced form way for Bayesian updating to inform the econometric specification. In the remainder of the paper we demonstrate how this can influence preferences and public good willingness to pay estimates.[14] The method developed in this paper is widely applicable to both stated and revealed preference data.[15]

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

[14] 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.

[15] Insofar as this model allows for scale heterogeneity across individuals, it builds on Train et al. (2005) and Scarpa et al. (2008b), which could also potentially allow for adding similar experience related controls.

distributed[16] and that the individual scale parameter is log-normally distributed[17] leads to the 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:

$$U_{ijt} = \left(\sigma_i \left(\mathbf{b} + \mathbf{\upsilon}_i\right)\right)' \mathbf{x}_{ijt} + \varepsilon_{ijt} \ , \tag{5}$$

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 $\mathbf{\upsilon}_i$. The new subscript t represents different choice tasks the same respondent may face – in discrete choice experiments an individual is confronted with a sequence of 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 experience in a random utility model. Therefore, 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 $(\mathbf{z})$ as covariates or means and variances of random taste parameters $\boldsymbol{\beta}_i \sim MVN\left(\mathbf{b} + \boldsymbol{\phi}'\mathbf{z}_i, \mathbf{\Sigma}\exp\left(\boldsymbol{\psi}'\mathbf{z}_i\right)\right)$ and/or as covariates of random scale and its variance

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

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

$\sigma_i \sim LN\left(1+\boldsymbol{\phi}'\mathbf{z}_i, \tau+\boldsymbol{\xi}'\mathbf{z}_i\right)$.[18] 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. Further, while the theoretical model predicts scale should increase in experience and scale variance should decrease with experience, thereby decreasing the magnitude of the error term relative to the deterministic portion of the utility, we do not restrict parameters estimates thereby permitting any relationship between experience and the parameters of interest. Finally, we do not have exogenous variation in experience. People who prefer the good more than others typically are observed as having a higher measured level of experience. Rather, our model tests and controls for learning through experience.[19] We cannot make causal inference about the effect of experience on preferences.

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:

$$
\begin{aligned}
&\Pr\left(y_{it}=j\right)=\frac{\exp\left(\exp\left(\sigma_i\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i+\boldsymbol{\upsilon}_i\right)\right)'\mathbf{x}_{ijt}\right)}{\sum_{k=1}^{J_{it}}\exp\left(\left(\sigma_i\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i+\boldsymbol{\upsilon}_i\right)\right)'\mathbf{x}_{ikt}\right)}\\
&\text{where:}\\
&\sigma_i=\bar{\sigma}+\boldsymbol{\phi}'\mathbf{z}_i+\tau\exp\left(\boldsymbol{\xi}'\mathbf{z}_i\right)\varepsilon_{0i} \qquad .\\
&\boldsymbol{\upsilon}_i=\boldsymbol{\Gamma\Omega\varsigma}_i\\
&\boldsymbol{\Omega}=diag\left(\mathbf{s}\right)\exp\left(\boldsymbol{\psi}'\mathbf{z}_i\right)
\end{aligned}
\tag{6}
$$

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

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

[19] Put another way, if agents do update their preferences with additional consumption experiences then a G-MNL model which does not control for learning in a theoretically motivated way is misspecified.

by averaging over D draws from the assumed distributions (Revelt et al., 1998). As a result, the simulated log-likelihood function becomes:

$$\log L = \sum_{i=i}^{I} \log \frac{1}{D} \sum_{d=1}^{D} \prod_{t=1}^{T_i} \frac{\exp\left(\left[\sigma_{id}\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i+\boldsymbol{\upsilon}_{id}\right)\right]'\mathbf{x}_{ijt}\right)}{\sum_{k=1}^{J_{it}} \exp\left(\left[\sigma_{id}\left(\mathbf{b}+\boldsymbol{\phi}'\mathbf{z}_i+\boldsymbol{\upsilon}_{id}\right)\right]'\mathbf{x}_{ikt}\right)}. \tag{7}$$

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 experience 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 also significantly affect scale and scale variance heterogeneity, alongside previous levels of experience with a good. 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. In both cases, we describe the public good and choice experiment before describing our proxy for experience in each dataset.

4.1. Case study 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 (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). 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 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 told 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 (thus stressing the consequentiality of choices). Six choice cards were given to each respondent. 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., 2008a). The parameters of this distribution were derived from a preliminary model estimated on data available from a pilot study.[20] The final design consisted of 8 questionnaire versions, each with 6 choice cards per respondent. Two samples were obtained from a

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

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.[21] There was, though, a consistent set of objective information presented to all respondents.

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 and (iii) how the conservation conflict with grouse shooting is managed. 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' experience with the good. We are comfortable using this as a proxy for experience since the uplands is the exclusive home to this species, and visiting upland sites is the most obvious way in which people can experience these birds in their habitat.

4.2. Case study 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 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

[21] 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.

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. The current revisions to the Directive relate to greater restrictions upon the standards for bathing water. The attributes chosen for the DCE describe three relevant aspects of coastal water quality: benthic health, human health risks, and beach debris. For each aspect, respondents were able to select between no change to the existing policy, a small change and a large change. Appendix B describes the three aspects in more detail. The per visit cost to an individual of visiting a beach with a given set characteristics (the costs of travel to the site) was used as the 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' experience with the good "coastal water quality" which we used was the reported number of days spent at the beach each year $(bdays)$. We are confident that number of days spent at the beach per year is a good proxy for experience here as beach quality is visually observable. It is also in the interest of beach goers to find out about water quality measures for health reasons before they enter the sea to go swimming or surfing, and such information is displayed on-site at designated beaches as part of a requirement of the Bathing Waters Directive.

It should be noted that in both studies, our measures of familiarity, namely number of visits to the uplands and to 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 consistent with the data.

5. Results

We now turn to the analysis of data collected in the two empirical studies. 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. For both studies we briefly discuss important features of the policy covariates before discussing coefficient estimates for our experience proxies and their implications.

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 1a and 2a.

The attributes related to the choice variables of the raptor conservation model (Table 1a) include alternative specific constants associated with different protection programs (LAW, $FEED$, $MOVE$), dummy-coded levels of population change of hen harriers (HH_1, HH_2) and golden eagles (GE_1, GE_2), and a continuously coded cost (FEE). The parameters were allowed to be information set-specific (superscripts on variable names indicate the two different samples), except for cost (FEE), which was constrained to be equal in both studies.[22] As a result, the vector of the attributes was:

$$\begin{aligned}\mathbf{X} = \; & LAW^1, FEED^1, MOVE^1, HH_1^1, HH_2^1, GE_1^1, GE_2^1, \\ & LAW^2, FEED^2, MOVE^2, HH_1^2, HH_2^2, GE_1^2, GE_2^2, FEE\end{aligned} \tag{8}$$

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 due to different presentation of information provided to respondents.

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 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:

[22] 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.

$$\mathbf{X} = SQ, BH_1, BH_2, HR_1, HR_2, DM_1, DM_2, FEE \quad . \tag{9}$$

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.

Table 1a shows the estimates in the raptor study. 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 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).

Turning to our experience proxies, increases in the measure of experience used here, namely the number of visits to Scottish uplands in the last 12 months (*visit*), increased respondents' mean scale parameters. Insofar as visits to the Scottish uplands proxy for experience, a larger scale parameter implies that respondents who were more familiar with uplands made statistically significant more deterministic choices. Recall that the scale parameter divides the error term. Therefore, if the scale parameter increases then the magnitude of the error term relative to the deterministic portion of utility decreases.[23] At the same time, *visit* significantly decreased scale variance, indicating that the scale parameters of respondents who had more experience became more similar (e.g., a decrease in scale heterogeneity). In sum, 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.

Table 2a presents estimates from the water quality study. 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 of Bayesian updating developed in Section 2.

In order to investigate the importance of controlling for experience we estimated the models presented in Table 1a and 2a without the experience-related covariates of scale and its variance. The results are presented in Table 1b and 2b, respectively. We found that although the model fit (in terms of the value of the log-likelihood function, McFadden's pseudo-R^2 and the Akaike Information Criterion) is better

[23] Refer to equation (4) and the description of the parameters in the equation for a precise definition of the scale parameter.

when the effects of experience on respondents' scale are taken into account, the overall results are quite similar – there were no substantial changes in model parameters or their significance.

To investigate this issue further, we calculated implicit prices associated with the attribute levels used in each study. Since the price coefficient in our studies was assumed random, the ratio distribution resulting from dividing each random, normally distributed parameter associated with the attribute levels with the random, normally distributed cost coefficient does not have finite moments, i.e. no mean and standard deviation of the empirical (Cauchy-like) distribution of WTP exist (Hinkley, 1969). For this reason, we calculated median WTP, along with its simulated standard error, and the 0.025 and 0.975 quantiles as proxies of the 95% confidence interval. In order to do so we adopted the following simulation method, based on the Krinsky and Robb parametric bootstrapping technique:

(1) we took 10,000 multivariate normal draws from the estimated vector of model coefficients and the associated variance-covariance matrix;

(2) for each of the draws we used numerical methods to solve the integral equations associated with equating the cumulative distribution function of a ratio distribution, resulting from dividing two bivariate normal variables, to 0.5, 0.025 and 0.975, thus calculating the median and the two quantiles;

(3) the standard error associated with the estimated median WTP was calculated using the sample of 10,000 draws.

The resulting WTPs are presented in Table 3 and 4 for the raptor conservation and the water quality studies respectively. In addition, we calculated the implicit prices for the models that incorporated experience-related scale coefficients, as well as the models that did not, thus allowing for a comparison of estimated WTP values with and without controls for experience.

Table 3 shows the median WTP estimates for the raptor conservation study. This study compares three policy alternatives for public good management (LAW, FEED and MOVE) across two different samples. Adding experience-related covariates to the scale variance term moderately decreased the median willingness to pay for all management practices in the first survey and moderately increased median willingness to pay for all management practices in the second. However, the change is sufficiently large so that within a regression specification median willingness to pay for one of the three management practices, MOVE, becomes statistically different at the 95% level across surveys. A second management practice, FEED, becomes statistically different at the 10% level. Further, when experience covariates are added, the same two management options, MOVE and FEED, are no longer significantly different from zero. More generally, Table 3 shows that adding experience controls to the scale parameter decreases the variance of median WTP estimates in the raptor conservation study.

Table 4 shows the median WTP estimate for the water quality study. This study also compares three different policy interventions for a public good across two surveys. In contrast to the Raptor study, the median WTP estimates are very stable when experience is or is not included as a covariate for scale and scale variance. Both the magnitudes across econometric models and the WTP estimates within models are similar. Further, adding experience related covariates to the water quality study do not significantly decrease the variance of median WTP estimates.

Jointly, Table 3 and Table 4 show that adding experience as a scale variance covariate can affect policy recommendations in demand estimation for public goods. While the median WTP estimates from including versus excluding experience-related covariates cannot be tested as statistically different from each other since the models are separately estimated, comparing the median and standard deviation of willingness to pay estimates for different policies is still instructive. In the case of the Raptor study, adding the experience covariates makes estimates of median willingness to pay for some management policies not statistically different from zero (FEED^1 and MOVE^1). No such difference occurs in the water quality study.

It is not unreasonable that there could be different effects across studies from allowing experience to affect scale and scale variance. If experience decreases the magnitude of the error term (e.g., scale increases), then more experienced survey participants may receive more weight in estimating the model's parameters since inexperienced participants survey responses are more likely to be attributed to the idiosyncratic portion of the random utility function. For example, if experienced respondents truly have a wide WTP distribution for a particular policy intervention relative to inexperienced participants, then we might expect to observe exactly the discrepancy between willing to pay estimates in Table 3 of the raptor conservation study. Specifically, the WTP for certain policies have relatively larger error bounds when experience is included. Alternatively, if experienced respondents have a similar WTP distribution to inexperienced respondents, then we would expect no difference, such as we observe in the water quality survey. The relative importance of experience in estimating WTP for a given policy, then, could be intimately related to respondents' priors, the relative amount of learning which occurs from our experience proxies (e.g., visits to location), and the true distribution of WTP when consumers have full information about their preferences. As a result, whether a public good or quasi-public good has measures of experience that are more or less informative likely affects how important controlling for experience is. Indeed, this is a fruitful area for future research.

Lastly, while there is no clear theoretical reasons for doing so, consider the implications of adding experience related covariates to the right hand side of the random utility model. We do not report the results here although they are available upon request, but we re-estimated the model including experience related covariates on mean willingness to pay for various policies for both studies. They are insignificant in all cases but two policy options in the water quality study (SQ and FEE). Finally, likelihood ratio tests show that adding experience related covariates to means does not improve the fit of the models in any significant way. Taken together, this is evidence that the theoretical model foundations in section two provide the correct structure to control for experience in a G-MNL model in these datasets.

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 of public goods for which market data does not exist. We offer a theoretical model which shows that, in effect, not permitting scale and scale variance to vary with experience amounts to misspecification of the structure of the error term in random utility model. We then develop and estimate a reduced form econometric model of demand estimation which both extends the generalized multinomial logit model and is consistent with this Bayesian 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).[24] 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. The 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 since our results are not causal. Other models posited by the literature include behavioral models such as

[24] 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.

confirmatory bias and rational inattention (Rabin et al., 1999; Gabaix et al., 2006). Second, while we offer on theoretically consistent econometric model that controls for experience level, there are potentially other models yet to be implemented. Third, we can make no claims as to the causal effect of experience and learning on WTP. The causal effect of learning on WTP for public goods and policy options which change the supply of such goods is a question which requires further empirical work.

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

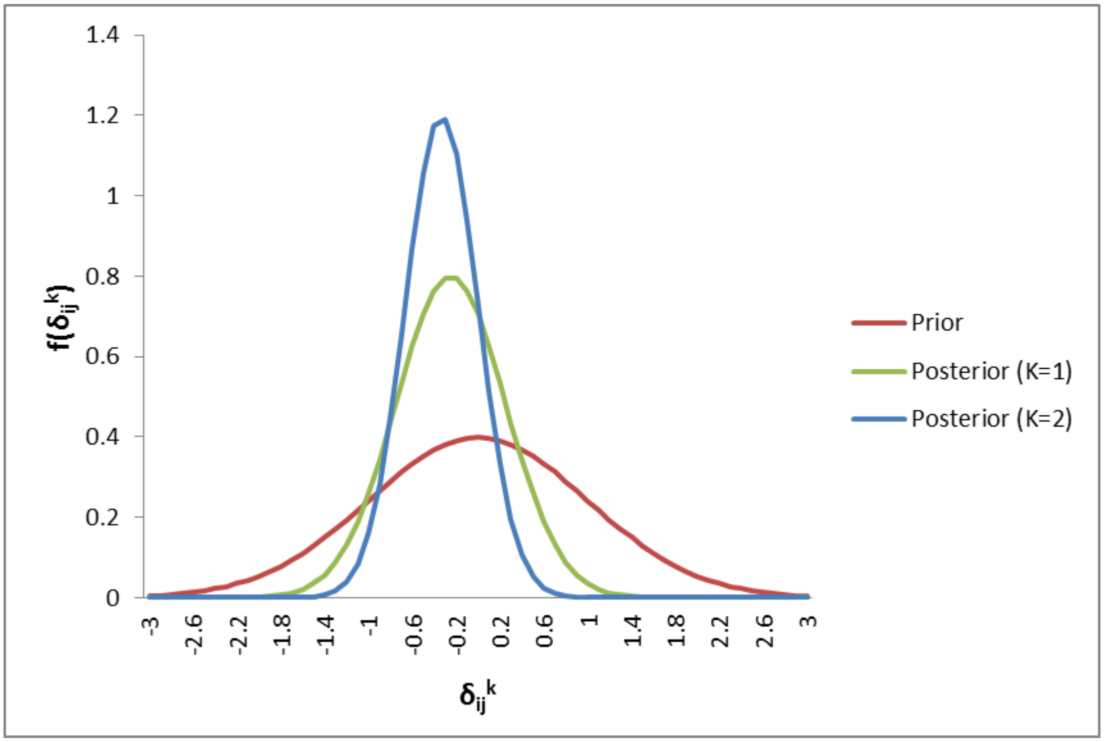

Figure 2. Example choice card from hen harrier survey

	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 1a. The discrete choice model results for the raptor conservation study with experience related covariates

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*		1.6368				
n (observations)		3450				
k (parameters)		91				

Table 2a. The discrete choice model results for the water quality study with experience related covariates

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	1.4492					
n (observations)	4366					
k (parameters)	51					

Table 1b. The discrete choice model results for the raptor conservation study with no experience related covariates

Variable	Mean			Standard deviation		
	coeff.	s.e.	p-value	coeff.	s.e.	p-value
LAW^1	11.8814	3.6265	0.0011	14.2713	4.2589	0.0008
$FEED^1$	11.8421	3.6601	0.0012	13.9818	4.1263	0.0007
$MOVE^1$	11.6177	3.6177	0.0013	14.1503	4.1624	0.0007
HH_1^1	4.0258	0.9629	0.0000	4.5505	1.1276	0.0001
HH_2^1	4.5305	1.0039	0.0000	4.8843	1.1855	0.0000
GE_1^1	5.0556	1.0834	0.0000	3.9848	0.9693	0.0000
GE_2^1	6.1169	1.2642	0.0000	4.7024	1.2319	0.0001
LAW^2	11.0122	2.3283	0.0000	10.8440	2.1037	0.0000
$FEED^2$	11.5288	2.3369	0.0000	11.8687	2.1516	0.0000
$MOVE^2$	10.3414	2.3918	0.0000	11.5853	2.0328	0.0000
HH_1^2	3.0174	0.7761	0.0001	7.6331	1.3856	0.0000
HH_2^2	3.5164	0.7306	0.0000	7.2480	1.3135	0.0000
GE_1^2	5.2731	1.0220	0.0000	8.1359	1.5295	0.0000
GE_2^2	6.1434	1.1003	0.0000	8.1513	1.4491	0.0000
FEE	-8.8150	1.9486	0.0000	14.0483	2.3986	0.0000
	Scale variance parameter (τ)					
	coeff.	**s.e.**	**p-value**			
τ	7.2005	0.9822	0.0000			
	Covariates of scale (σ)			**Covariates of scale variance (τ)**		
	coeff.	**s.e.**	**p-value**	**coeff.**	**s.e.**	**p-value**
study	0.7208	0.2616	0.0059	-0.2628	0.0496	0.0000
	Model characteristics					
Log-likelihood	-2736.2703					
McFadden's pseudo R^2	0.4279					
AIC/*n*	1.6378					
n (observations)	3450					
k (parameters)	89					

Table 2b. The discrete choice model results for the water quality study with no experience related covariates

Variable	Mean			Standard deviation		
	coeff.	s.e.	p-value	coeff.	s.e.	p-value
SQ	-2.1881	0.3753	0.0000	3.7663	0.5037	0.0000
BH_1	0.7266	0.1220	0.0000	0.6133	0.1808	0.0007
BH_2	1.0497	0.1640	0.0000	1.3721	0.2578	0.0000
HR_1	0.7389	0.1459	0.0000	1.2229	0.2113	0.0000
HR_2	1.0269	0.1732	0.0000	1.5932	0.2500	0.0000
DM_1	1.1190	0.1489	0.0000	1.4668	0.3038	0.0000
DM_2	1.3699	0.1504	0.0000	1.5026	0.4292	0.0005
FEE	-0.3381	0.0320	0.0000	0.3931	0.0416	0.0000
	Scale variance parameter (τ)					
	coeff.	s.e.	p-value			
τ	2.0094	0.4208	0.0000			
	Model characteristics					
Log-likelihood	-3116.2321					
McFadden's pseudo R^2	0.3358					
AIC/n	1.4499					
n (observations)	4366					
k (parameters)	49					

Table 3. Implicit prices for the raptor conservation study

	Model **with** experience related covariates			Model **without** experience related covariates		
	median	s.e.	95% c.i.	median	s.e.	95% c.i.
LAW^1	21.83	10.5519	2.52 – 44.06	26.40	12.3651	5.25 – 53.27
$FEED^1$	17.00	10.3418	-1.65 – 38.97	25.29	12.2705	4.22 – 51.88
$MOVE^1$	14.99	10.4744	-4.08 – 37.01	23.47	12.1938	2.33 – 49.90
HH_1^1	13.27	5.4750	2.59 – 24.22	16.59	4.7052	7.13 – 25.78
HH_2^1	13.10	4.9696	3.08 – 22.59	16.26	4.6003	6.81 – 25.14
GE_1^1	21.11	5.8122	9.64 – 32.35	24.72	4.8489	14.88 – 33.87
GE_2^1	21.34	5.7622	9.74 – 32.27	25.71	4.9880	15.27 – 35.05
LAW^2	50.06	12.8543	28.58 – 79.02	46.21	14.1695	23.49 – 79.00
$FEED^2$	58.85	13.2612	37.17 – 88.98	53.54	14.6885	30.25 – 88.40
$MOVE^2$	58.65	12.6048	37.97 – 87.41	52.75	14.6233	29.37 – 87.24
HH_1^2	20.86	5.1928	9.64 – 29.93	22.03	5.5040	10.59 – 32.17
HH_2^2	20.03	5.2451	8.73 – 29.22	21.17	5.1209	10.55 – 30.66
GE_1^2	30.58	5.7398	17.64 – 40.54	31.80	5.7249	19.61 – 42.24
GE_2^2	33.21	5.8140	20.15 – 43.00	34.15	5.8234	21.70 – 44.73

Table 4. Implicit prices for the water quality study

	Model **with** experience related covariates			Model **without** experience related covariates		
	median	s.e.	95% c.i.	median	s.e.	95% c.i.
SQ	-2.59	0.6543	-3.88 – -1.35	-2.78	0.6884	-4.10 – -1.52
BH_1	1.27	0.2649	0.77 – 1.83	1.26	0.2675	0.76 – 1.80
BH_2	1.92	0.3954	1.19 – 2.75	1.84	0.3842	1.14 – 2.59
HR_1	1.14	0.3701	0.41 – 1.87	0.94	0.3719	0.21 – 1.68
HR_2	1.38	0.4416	0.49 – 2.24	1.19	0.4589	0.31 – 2.07
DM_1	1.60	0.3945	0.81 – 2.39	1.49	0.4322	0.64 – 2.34
DM_2	2.23	0.3610	1.43 – 2.91	2.25	0.4434	1.26 – 2.99

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.

Appendix B

This section describes the specific aspects of the water quality study in detail.

Benthic Health

Measures taken as part of complying with the revised directive will impact 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 chances 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 (the average current risk level in UK bathing waters 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.