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Valuing spatially dispersed environmental goods: A joint revealed and stated preference model to consistently separate use and non-use values

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Valuing spatially dispersed environmental goods: A joint revealed and stated preference model to consistently separate use and non-use values

by

**Silvia Ferrini, Carlo Fezzi, Brett H. Day,
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**VALUING SPATIALLY DISPERSED ENVIRONMENTAL GOODS: A JOINT
REVEALED AND STATED PREFERENCE MODEL TO CONSISTENTLY
SEPARATE USE AND NON-USE VALUES**

by

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Abstract

We argue that the literature concerning the valuation of non-market, spatially defined goods (such as those provided by the natural environment) is crucially deficient in two respects. First, it fails to employ a theoretically consistent structural model of utility to the separate and hence correct definition of use and non-use values. Second, applications (particularly those using stated preference methods) typically fail to capture the spatially complex distribution of resources and their substitutes within analyses, again leading to error. This paper proposes a new methodology for addressing both issues simultaneously. We combine revealed (travel cost) and stated preference (choice experiment) data within a random utility model formulated from first principles to yield a theoretically consistent distinction between the use and non-use value of improvements in a non-market natural resource. The model is specified to relate both types of value to the attributes of the good in question including the spatial arrangement of the resource under consideration and its substitutes. We test the properties of the model using data simulated from a real world case study examining an improvement of open-access waters to good ecological standards. Through a Monte Carlo experiment we show that both use and non-use parameters can be precisely estimated from a modest sample of observations.

Keywords: Non-market preferences; Environmental Valuation; Use and non-use values; Revealed preference; Stated preference; Travel cost; Choice Experiments

1. INTRODUCTION

In this paper we propose and test a random utility model designed to distinguish and estimate, within a single, theoretically coherent framework, the use and non-use value of a non-market public good. Assessment of non-use values is crucial in order to correctly estimate the value of such goods, and distinguishing between use and non-use is necessary to design well-targeted policies (Krutilla, 1967; Greenley *et al.*, 1981; Arrow *et al.*, 1993; Freeman, 2003). However, recent research and public enquiries have questioned the often unsubstantiated emphasis placed upon non-use values (ENDS, 1998; Moran, 1999; Bateman *et al.*, 2006).

The paper also sets out to tackle the issues raised by the uneven availability and complex spatial distribution of substitute resources. Within any given valuation study one could argue that this is not an issue which needs specific attention as substitute availability is captured within the value of the status quo. However, many environmental valuation studies fail to be specific regarding the actual location under consideration. For example, some choice experiment studies will provide values for distances to recreational sites, but not their actual location (Boxall *et al.* 1996; Hanley *et al.* 2002), meaning that substitute availability is unclear. This seems likely to induce uncertainty within respondents which in turn may well affect valuations. Furthermore, it undermines subsequent efforts to use results for transferring benefits estimates to other areas with differing substitute availability and distribution. We seek to address this issue through development of a spatially explicit valuation methodology which we argue should provide more robustly transferable results.

In order to motivate our work and provide a policy context of clear contemporary importance we present a case study focusing upon improvements in the quality of open-access waters to good ecological status, an end point prescribed as part of the recent EU Water Framework Directive (WFD) (European Commission, 2000)¹. A geographical information system (GIS) is used to capture the physical characteristics (including substitute availability) of a real-world case study area. A simulation exercise is undertaken through which a Monte Carlo analysis indicates that our model allows clear identification of use and non-use values and their relation to site attributes using a reasonably sized sample of responses.

¹ The WFD requires all EU member states to achieve “good ecological status” in their water bodies by 2015. This ambitious target is likely to involve major policy change, aimed at reducing pollution from both diffuse and point sources. These improvements will have effects on both environmental quality and human wellbeing. However, the cost of such changes is expected to be substantial with costs just in the UK of £450-630 million per year throughout the period of implementation (ENDS, 2008). Since the WFD allows exemptions from the implementation of improvements in cases of “disproportionate costs” (RPA, 2004), estimating the benefits arising from water quality improvements assumes crucial policy relevance and has been already subject of extensive debate (Bateman *et al.* 2006, Hanley *et al.* 2006, Birol *et al.* 2006).

Non-market values of natural resources or public goods have traditionally been estimated using revealed preference (RP) or stated preference (SP) methods (Champ et al., 2003). RP approaches, such as the travel cost method, use behavioural observations to estimate the willingness to pay (WTP) for spatially defined goods (typically recreational sites) characterized by a diversity of attributes (including the travel time between a user's outset location and the destination). Such behavioural data permits the identification of use but not non-use value. In contrast, SP approaches, such as choice experiments or the contingent valuation method, ask the individual to make hypothetical choices that can be formulated to identify total values given by the sum of use and non-use values.

Both RP and SP approaches have advantages and drawbacks. However, the strengths of RP methods are typically the weaknesses of SP techniques and vice versa (McFadden, 1994; Whitehead *et al.*, 2008). The combination of the two methods to jointly estimate RP and SP data has been proposed as a possible solution to mitigate the shortcomings and fully exploit the potential of both techniques. This combined approach has been established in transportation research (Ben-Akiva and Morikawa, 1990), marketing (Hensher and Bradley, 1993) and environmental economics (Adamowicz *et al.*, 1994). However, when evaluating public goods such as natural resources, the combination of both methods has often lead researchers to focus on use values, neglecting or only partially exploring the non-use values of the good under investigation (e.g. Adamowicz *et al.*, 1994; Niklitschek and Leon, 1996; Huang *et al.* 1997).

Recently, Eom and Larson (2006) provide a consistent model of preferences to estimate use, non-use and total value of quality changes combining RP (travel cost) and SP (contingent valuation) data. Their approach is based on integrating back a Marshallian recreation demand function to recover the implied quasi-expenditure function and thereby identifying non-use value. Estimating jointly the recreation demand (from travel cost data) and WTP (from contingent valuation data) they provide a coherent framework to estimate use, non-use and total value. However, their approach is based solely upon behavioural recreation data and can only be estimated through interviewing the users of the natural resource, thereby omitting the values of non-users who are likely to constitute the majority of the population and may hold sizeable values for the resource in question. In addition, Eom and Larson's model is formulated for a single recreational site and assumes a frequency of visitation that might appropriately be modelled as a continuous demand function. Furthermore, the technique is affected by well known difficulties concerning the imputation of travel cost values (Randall, 1994).

In this paper we propose a unifying framework to estimate and distinguish between the use and non-use value of a natural resource within a random utility model that combines RP (travel cost) and SP (choice experiment) data. Our technique is appropriate for situations characterised by a multiplicity of substitute sites and relatively low frequency of visitation; a pattern of recreational use often observed in the real world. Compared to the approach proposed by Eom and Larson (2006), our methodology is more flexible because: (a) it explicitly addresses the substitution possibilities raised by multiple sites, (b) it considers the values held by both users and non-users of a natural resource and (c) it allows the researcher to estimate the contributions of the different attributes of a resource to both use and non-use values. Furthermore, our model is immune from Randall's (1994) critique since it does not rely upon a researcher-assigned money value for the individual's travel time.

This paper is organized as follows: Section 2 presents the theoretical basis of our model, illustrates its formulation within a general random utility framework and discusses the estimation method; Section 3 briefly discusses strategies developed to permit the elicitation of necessary data within a subsequent field trial of our methodology while Section 4 presents an application to the valuation of water quality improvement in the UK using data simulated from the characteristics of a real-world case-study area; Section 5 concludes by giving suggestions for further research.

2. THE USE AND NON-USE MODEL

A random utility model that separates use and non-use values should take into account the different nature of these values. Use value is related to the individual's ability to directly enjoy (consume) the natural resource in some consumption period. In contrast non-use value is independent of such direct consumption. Considering use values we can distinguish two periods of consumption; the present day and some future period. If we analyse the present period recreational choice then the individual's preferences, their budget constraint and the characteristics of a potential trip (e.g. weather conditions) are all known to the respondent and she determines her use value with certainty. However, if we ask the same respondent to evaluate recreational choice for the future period then some of this information becomes unknown to the individual and she cannot determine use value exactly. The model developed subsequently incorporates this uncertainty relative to the time of consumption.

2.1 The economic model of choice

In considering a geographically dispersed natural resource, we can define a behavioural model describing the utility that an individual could attain within each time period from a specific state of the world, where a state of the world s ($s = 1, \dots, S$) is characterized by a particular mosaic of natural attributes. Within the geographical area there exist K ($k=1, \dots, K$) locations which provide different levels of benefits according to the state of the world. These locations can provide both non-use and use benefits if they are accessible or just non-use utility if they cannot be visited. Therefore, we can assume that in the geographical area there exist J ($j=1, \dots, J$) accessible sites where J can be equal to or smaller than K .

Considering the individual behavioural model, we assume that in any one time period (for sake of argument 1 year) respondent i is faced with T_i ($t=1, \dots, T_i$) choice occasions and in each t she may or may not take a trip to one of the J accessible sites including the no trip option as $j = 0$.²

The individual choice is influenced by the vector of site attributes $\mathbf{x}_{j,t}$, (which is constant across respondents but can change over time period, e.g. fish species present at the site, recreational facilities, etc.), the distance to the site for individual i ($d_{i,j}$), a vector of preference parameters ($\boldsymbol{\theta}_i^{Use}$) and a structural error term ($\boldsymbol{\varepsilon}_{i,j,t}^{Use}$) representing the individual's inability to perfectly predict the utility of a trip to site j . This latter term represents the uncertainty related to the time of consumption and is specific to the use value.

The utility derived from visiting site j in period t for individual i is formally defined as:

$$(1) U_{i,j|t}^{Use} = f(\mathbf{x}_{j,t}, d_{i,j}, \boldsymbol{\theta}_i^{Use}, \boldsymbol{\varepsilon}_{i,j,t}^{Use}).$$

Considering that the individual i values the use benefits for options J with uncertainty, $\boldsymbol{\varepsilon}_{i,j,t}^{Use}$, we can assume that the expected maximum utility for individual i is as in eq. (2).

$$(2) E[U_{i,t}^{Use}] = E\left[\max_j f(\mathbf{x}_{j,t}, d_{i,j}, \boldsymbol{\theta}_i^{Use}, \boldsymbol{\varepsilon}_{i,j,t}^{Use})\right].$$

² For simplicity, we remove the index s in the following equations.

The functional form of (2) will vary according to assumptions regarding the structural error term $\varepsilon_{i,j,t}^{Use}$ and the equation collapses to the standard utility function under the assumption of certainty in the present period.

In each time period, state of the world s may also endow individual i with utility simply from the existence of a given natural resource. This value is determined by the aggregate non-use characteristics of the natural resources $y_{k,t}$ across the whole geographical region (e.g. preservation of endangered species, characteristics of protected areas, etc.) and is independent of whether sites are accessible or not and of the proximity of those sites to an individual's home. Therefore this value is not linked to the time of consumption and individual i values it without uncertainty.

The utility value derived from the existence of the K natural resources over the geographical area is defined as:

$$(3) U_{i,t}^{NoUse} = g(y_{1,t}, \dots, y_{K,t}; \theta_i^{NoUse}).$$

Given the state of the world s , the expected use benefits (2), the existence value (3), the individual's income level (W) and its parameter value γ described by the function $h(W_i, \gamma)$, we can define the individual's *a-priori* assessment of the expected total value derived from natural resources over a geographical region as:

$$(4) E[TV_i] = \sum_{t=1}^{T_i} \left\{ E \left[\max_j f(\mathbf{x}_{j,t}, d_{i,j}, \theta_i^{Use}, \varepsilon_{i,j,t}^{Use}) \right] \right\} + g(y_{1,t}, \dots, y_{K,t}; \theta_i^{NoUse}) + h(W_i, \gamma)$$

Equation (4) describes the individual behaviour in valuing natural resources when the location of those resources and substitution across sites are likely to be pertinent. This structural model incorporates issues concerning the time of consumption and uncertainty in the evaluation task.

The next step is to operationalise this model through econometric implementation. There are three main issues arise here: defining a functional form for $U_{i,t}^{Use}$ and $U_{i,t}^{NoUse}$, the assumption regarding the structural error term, and finally the treatment of the econometric error term which captures unobservable factors.

2.2 The econometric specification

An immediate issue is that the econometric model can differ according to the evaluation method used to observe individual behaviour. Therefore, the functional form for $U_{i,t}^{Use}$ and $U_{i,t}^{NoUse}$ remain unspecified in this section and will be considered within the case study described in section 4 of this paper.

In order to describe the econometric model, we can start with a standard choice experiment framework to derive a random utility model which distinguishes use and non-use values. The policy scenarios s ($s = 1, \dots, S$) are characterized by a particular mosaic of natural resource improvements over a geographical area. The attributes of the K locations change with the policy scenario description. Some of these locations are accessible (J) providing both use and non use values however other sites ($K-J$) are inaccessible and offer only non-use benefits.

The benefit provided by visiting a given recreational site j is assumed to be determined by the site attributes $x_{j,s}$ (determined in part by the scenario s) and the cost of travel to that site, $d_{i,j}$. The non-use value is defined as in (3) and we assume that each scenario (s) is characterized by a cost (P) payable by the individual.

In such a framework, the expected total utility function depends on the specification of the structural error term in eq. (2). The $\varepsilon_{i,j,t}^{Use}$ error term represents the individual's uncertainty regarding the utility of visiting site j at time t in scenario s . This uncertainty arises from various unforeseen circumstances such as weather conditions, chaotic traffic, etc. There is no clear functional form for this error and so we assume that it is an independent and identically distributed (iid) Gumbel function $(0, \square)$. Therefore, following Ben-Akiva and Lerman (1985), we can re-write eq. (2) using the expression of the maximum of iid Gumbel variables as³:

$$(5) E[U_{i,t}^{Use}] = \lambda \log \left(\sum_{j=0}^J \exp \left(\frac{1}{\lambda} f(\mathbf{x}_{j,t}, d_{i,j}, \boldsymbol{\theta}_i^{Use}) \right) + \frac{E}{\lambda} \right)$$

where E is the Euler constant, the sum over j captures characteristics of all substitutes and \square is the scale parameter of the structural error term. This specification implicitly takes account of the substitution effect across sites. In fact, treating the study area as a policy

³ This assumes all the residuals to be iid across the sites J in the same scenario.

scenario s with separate recreation sites, we can examine the preferences for spatial distributed sites at different quality levels. In other words, with this formulation we explicitly acknowledge the role of substitutes in the choice.⁴

Substituting (5) in eq. (4) and including the econometric error term $e_{i,s}$ we can define the expected total utility value attached to each scenario s :

(6)

$$E[TV_{is}^{CE}] = \sum_{t=1}^{T_i} \left\{ \lambda \log \left(\sum_{j=0}^J \exp \left(\frac{1}{\lambda} f(\mathbf{x}_{j,s,t}, d_{i,j}, \boldsymbol{\theta}_i^{Use}) \right) + \frac{h}{\lambda} \right) + g(y_{k,s,t}; \boldsymbol{\theta}_i^{NoUse}) \right\} + h(I_i - P, \gamma) + e_{is}$$

The term $e_{i,s}$ is a choice specific error-term which encompasses those factors unobserved by the researcher such as characteristics of the structural error term, characteristics of the individual, non-included attributes of sites, measurement error and /or heterogeneity preferences. The error term is assumed to be *iid* Gumbel $(0, \mu)$ where μ represents the scale parameter of the econometric error term. This error term is indirectly linked to the structural error term $\varepsilon_{i,s,j,t}^{Use}$ and in the estimation we can only estimate one of the two.

Specifying a choice experiment in which each choice task is between S_{CE} possible scenarios at a time (with each scenario involving J recreational sites and the “anything else” option) then, following McFadden (1974), we can define the probability $\pi_{i,s}$ of respondent i choosing scenario s , when $\boldsymbol{\theta}_i^{Use} = \boldsymbol{\theta}^{Use}$ and $\boldsymbol{\theta}_i^{NoUse} = \boldsymbol{\theta}^{NoUse}$ and utility function (6) as per eq.(7):

$$(7) \pi_{i,s} = \frac{T_i \lambda \log \left(\sum_{j=0}^J \exp \left(\frac{1}{\lambda} f(\mathbf{x}_{j,s}, d_{i,j}, \boldsymbol{\theta}^{Use}) \right) \right) + g(y_{k,s}; \boldsymbol{\theta}^{NoUse}) + \gamma P_{i,s}}{\sum_{h=1}^{S_{CE}} T_i \lambda \log \left(\sum_{j=0}^J \exp \left(\frac{1}{\lambda} f(\mathbf{x}_{j,h}, d_{i,j}, \boldsymbol{\theta}^{Use}) \right) \right) + g(y_{k,h}; \boldsymbol{\theta}^{NoUse}) + \gamma P_{i,h}}$$

Assuming a linear specification for both $f(\mathbf{x}_{j,s}, d_{i,j}, \boldsymbol{\theta}^{Use})$ and $g(y_{k,s}; \boldsymbol{\theta}^{NoUse})$ the parameters of the model can be identified as per the classic conditional logit (with a non-linear utility function). In other words, parameter-specific intercepts can be estimated as the difference

⁴ In the current specification of the model we consider all the “outside good” substitutes as a “zero” option in the specification of function $f()$. However, we acknowledge that in so doing we may introduce a source of misspecification error that can be minimized introducing an individual-fixed effect. This specification could recover a parameter for the outside good for each individual and the size of that parameter would reflect the proximity and quality of “outside good” substitutes. Future research will focus on this.

from a base-line (for example, from the “anything else” option). However, those individual level variables parameters (e.g. the respondent’s income) which are constant across the s choice occasions cannot be estimated.

Developing the econometric model for travel cost data we obtain a slightly different specification. In this case the individual i values the J sites available in the current state of the world and visits the most preferred. Therefore, observing behaviour at the time of the visit choice removes sources of uncertainty (e.g. from variation in the weather) and eq. (1) becomes deterministic. Therefore, the total utility value derived from visiting site j (including an econometric error term v_i which encompasses those factors unobserved by the researcher) can be written as per eq. (8):

$$(8) \quad TV_i^{TC} = \max_j x \left(f \left(\mathbf{x}_{j,t}, d_{i,j}, \boldsymbol{\theta}_i^{Use} \right) \right) + \frac{g(y_k; \boldsymbol{\theta}_i^{NoUse}) + h(I_i, \gamma)}{T_i} + v_i.$$

The econometric error term in (8) follows *iid* Gumbel distribution with parameters $(0, \sigma)$. The scale parameter of this econometric error term differs from the scale parameter of the CE error term and reflects the respective levels of variation in the two different datasets due to the real and hypothetical choice (e.g. Adamowicz *et al.*, 1994).

Using eq. (8) we can write the probability ρ_i of respondent i undertaking a trip to site j considering the J options available ($j=0, 1, \dots, J$) where $j=0$ is the “anything else” option and $\boldsymbol{\theta}_i^{Use} = \boldsymbol{\theta}^{Use}$, as a standard conditional logit model:

$$(9) \quad \rho_i(j) = \frac{\exp \left[f \left(x_j, d_{i,j}; \boldsymbol{\theta}^{Use} \right) \right]}{\sum_{j=0}^J \exp \left[f \left(x_j, d_{i,j}; \boldsymbol{\theta}^{Use} \right) \right]}.$$

Note, that the behavioural model presented in the previous section is consistent with the traditional travel cost literature (Bocksteal and McConnell, 2007).

In order to improve the explanation power of our behavioural model we can combine the travel cost and choice experiment data within our estimation. This provides efficient estimates of the parameters of the utility function as discussed in Whitehead *et al.* 2008.⁵

⁵ We implicitly assume that the marginal utility of income (and of time) is the same in SP as it is in RP. This assumption may not hold perfectly but the findings of Carson *et al.* (1996) suggest that SP and RP values are highly correlated which supports this assumption.

Assuming that the CE data comes from a sample of N respondents ($i=1, \dots, N$) and TC data are taken from a differ sample of M respondents ($m=1, \dots, M$) we can combine equations (7) and (9) and jointly estimate via Maximum Likelihood (ML) the utility parameters. The likelihood of the joint model is:

$$(10) L = \sum_{i=1}^N \sum_{s=1}^S l_{i,s} \pi_i(s) + \sum_{m=1}^M \sum_{j=0}^J l_{m,j} \rho_m(j) ,$$

were the dummy variables $l_{i,s}$ and $l_{m,j}$ identify the choice of the individual concerned and $\pi_i(s)$ and $\rho_m(j)$ are defined as in (7) and (9). The first part of equation (10) represents the choice across policy scenarios S involving a quality change of all the K recreational sites. In contrast, the latter part of (10) represents the recreational choice for the single site j among the J sites. If $f(x_j, d_{ij}; \theta^{Use})$ is linear, the second part of the likelihood is globally concave (McFadden, 1974). However, even if both the use part $f(\mathbf{x}_{j,s}, d_{i,j}, \theta^{Use})$ and the non-use part $g(y_{k,s}; \theta^{NoUse})$ are linear, the specification of the $\pi_i(s)$ function still contains a non-linear term and therefore might contain local maximums. If the number of parameters in the use part is high, joint estimation might require both a global optimization algorithm and a substantial number of observations in order to provide meaningful estimates. In the next section, we evaluate the model performance in this regard. We use simulated data derived from the spatial characteristics of a real world area and consider a case-study concerning open-access water quality improvements. In so doing we show that the estimates via ML techniques, obtained through the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method implemented in R (R Development Core Team, 2004), provide satisfactory results for the model.

We are conscious that, in order to operationalise our methodology, we need to convey information on the level and spatial distribution of water quality across the case study area. Therefore, prior to presenting our simulation results, we briefly describe the manner in which we intend to present such information and gather responses within a future field trial of our methodology. This discussion also provides some background on the real world location and water quality changes considered within our subsequent simulation exercise.

3. CASE STUDY AREA AND THE DEVELOPMENT OF FIELD SURVEY TOOLS FOR CONVEYING INFORMATION ON THE LEVEL AND DISTRIBUTION OF WATER QUALITY

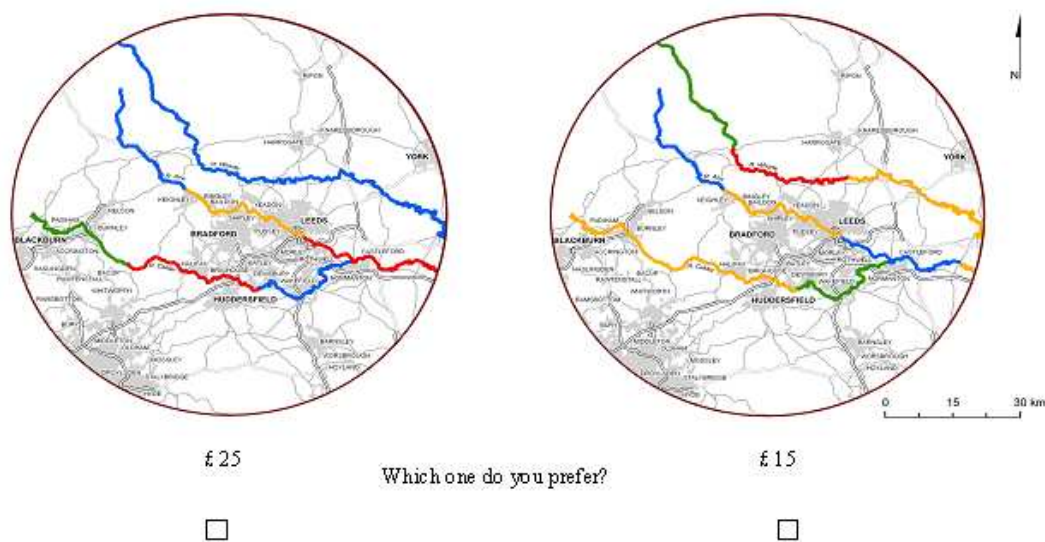
The aim of our current simulation exercise and planned field trial is to test the methodology and model described in the previous section, combining travel cost and choice experiment methods, within a real-world setting. While in principle we see no barrier to the application of our methodology to any area, in considering an informative case study for testing our methodology we sought an area in which there is a considerable variation in the geographical distribution of rivers with respect to individuals home locations and some diversity in water quality. Together this varies substitute availability and quality across the study area as well as assuring that the area is likely to be subject to water quality change as a result of the WFD. Because in subsequent work we wish to assess the impact of socioeconomic variation upon economic values we chose to base our case study in and around the cities of Bradford and Leeds and surrounding rural areas (more details can be found in Bateman et al. 2006). Located in the northern part of the UK Humber basin, this is a socio-economically diverse area cut through by three major rivers: Wharfe, Aire and Calder.

Our model requires that both travel cost and choice experiment data be gathered in a manner that allows the analyst to assess trade-offs between quality and cost in both formats. To elicit such data a custom written computer assisted interview program was written. Here the travel cost data was collected by presenting survey respondents with a touch screen map of the study area on which they indicate their home location and the location of any river sites they had visited within a specified period. In order to elicit respondents' subjective assessment of water quality at each site a novel water quality ladder was developed which conveys distinct levels of river quality in terms of its ecological and use attributes (Hime and Bateman, 2007). The ladder uses coloured labels to characterize four water quality levels with blue denoting pristine sites, green for good sites, yellow for fair sites and red for poor sites.

For the purpose of the choice experiment study, each policy scenario is again conveyed via maps. Here each river is divided into three stretches of roughly similar length with quality held constant within each of the resultant nine stretches, but varied across stretches. By depicting rivers using the colour code developed in the water quality ladder, respondents can see both the location and quality of each stretch of river under a given scenario. Policy change can then be depicted by changing the colouring of each stretch, thereby introducing variation in water quality and its availability into our study design. The choice experiment

proceeds by asking respondents to choose between different policy options. In our simulation and planned field trial simple pairwise choices are adopted to reduce cognitive loads upon respondents. In principle one could rely upon travel time alone to introduce the issue of cost⁶. However, additional information is gathered by adding an explicit cost to each option in the choice experiment. As usual in a choice experiment, respondents face a number of such choices. In the simulated choice experiment two strategies were assessed, the first using 12 pairwise choices while the second halving this number. An example of the map based pairwise choice format developed for the subsequent field trial is illustrated in Figure 1.

Figure 1: Example choice experiment question



By interviewing respondents with home locations distributed across the study area we ensure our study has variation in travel cost (both actual cost to currently visited sites and potential cost to sites that might be visited under different SP policy scenarios)⁷. This cost variation can readily be measured by generating all maps within a GIS. By recording the respondents' home address within the survey⁸ the GIS can subsequently calculate travel distances (Euclidean, or via road and path) and corresponding travel times from the respondents' home address to each point on all river stretches and to any of a myriad of substitute or complementary resources⁹.

⁶ Although this requires the assumption that travel costs are treated identically to explicit policy costs.
⁷ In ongoing work we examine the incorporation of distance within the optimal design of choice experiments.
⁸ If interviews are completed outside the respondents home address then any concerns regarding confidentiality or item non-response can readily be overcome by using the respondents full post code which, in the UK, yields a highly accurate estimate of home address. Several years of including such questions in surveys have shown that this yields very low item non-response within bone-fide academic research surveys.
⁹ Jones et al.(2002) use such a methodology to calculate travel distance and times to both those natural resources being transformed through policy implementation, other non-transformed natural resources and a host

4. A SIMULATION EXERCISE: THE BENEFITS OF OPEN-ACCESS WATER QUALITY IMPROVEMENTS

The aim of the simulation is to test the model described in the section 2. More technically, we propose a theoretically consistent specification of the role of use and non use within the indirect utility function of the parameters of which can be recovered efficiently through responses to a choice experiment coupled with data on actual recreation behaviour. The assumption is that the respondent i ($i=1, \dots, N$) in evaluating different policy scenarios will choose the option with the highest total value. The deterministic components of equation (1) per each j site in the choice occasion t are specified as follows:

$$f(\mathbf{x}_{j,t}, d_{i,j}, \boldsymbol{\theta}^{Use}) = \sum_{q=0}^4 I_{j,q,s} \alpha_q - \delta d_{i,j},$$

where $I_{j,q,s}$ is a dummy variable which describes the characteristics of the site given by the water quality level q (here expressed by the four river colours in Fig. 1) and it is used to isolate the intercept α_q for site j ($j=1, \dots, 9$) including the “anything else” option as $q = 0$; d_{ij} is the distance between the recreational site j and the i^{th} respondent’s home and $\boldsymbol{\theta}^{Use} = (\alpha_q, \delta)$ is the parameters vector. Following the assumption that the structural error term is *iid* Gumbel we can re-write eq. 5 as follow:

$$E[U_{i,t}^{Use}] = \lambda \log \left(\sum_{j=0}^J \exp \left(\frac{1}{\lambda} \left(\sum_{q=0}^4 I_{j,q,s} \alpha_q - \delta d_{ik} \right) \right) + \frac{E}{\lambda} \right)$$

The utility value derived from the existence of those sites is specified as:

$$g(y_{k,t}; \boldsymbol{\theta}^{NoUse}) = \sum_{q=1}^4 \beta_q w_{q,s},$$

where $w_{q,s}$ is the total quantity of water quality q within the map (here expressed as number of stretches at that quality level) and the utility parameter are $\boldsymbol{\theta}^{NoUse} = \beta_q$.

In simulating the data, we assume that the mid-point of each one of the nine stretches contains a recreational site whose water quality corresponds to that of the overall stretch. Furthermore, we assume a zero distance for the “anything else” use option and that, in the time period considered in the experiment, any individual has only one choice occasion

of other man-made resources (including zoos, amusement parks, cinemas, etc.) which may have substitute or complementary effects upon values for the focal resources.

(including the “anything else option”), i.e. $T_i = 1$. Thus the expected total value of option s for respondent i is now:

$$(11) \quad TU_{is} = \lambda \left(\ln \left[\sum_{j=1}^9 \exp \left[\frac{1}{\lambda} \left(\sum_{q=0}^4 I_{q,j,s} \alpha_q - \delta d_{ij} \right) \right] \right] \right) + \sum_{q=1}^4 \beta_q w_{q,s} + \gamma (I_i - P_{i,s}) + e_{is}$$

Here, the parameters α_q are the quality level specific intercepts, δ is the parameter identifying the disutility of distance and β_q are the non-use utility components of the quantity of river quality q . The probability of respondent i choosing option s in the choice experiment becomes:

$$(12) \quad \pi_i(s) = \frac{\exp \left[\lambda \left(\ln \left[\sum_{j=1}^9 \exp \left[\frac{1}{\lambda} \left(\sum_{q=0}^4 I_{q,j,s} \alpha_q - \delta d_{ij} \right) \right] \right) + \sum_{q=1}^4 \beta_q w_{q,s} + \gamma P_{i,s} \right] \right)}{\sum_{h=1}^2 \exp \left(\lambda \left(\ln \left[\sum_{j=1}^9 \exp \left[\frac{1}{\lambda} \left(\sum_{q=0}^4 I_{q,j,h} \alpha_q - \delta d_{ij} \right) \right] \right) + \sum_{q=1}^4 \beta_q w_{q,h} + \gamma P_{i,h} \right) \right)}$$

Considering the travel cost side, the probability that the last visit of respondent r ($r=1, \dots, M$) was to the stretch j is:

$$(13) \quad \rho_r(j) = \frac{\exp \left[\sum_{q=0}^4 I_{q,j} \alpha_q - \delta d_{ij} \right]}{\sum_{l=1}^9 \exp \left[\sum_{q=0}^4 I_{q,l} \alpha_q - \delta d_{il} \right]}$$

Combining equations (12) and (13) we obtain the likelihood function whose maximization provides the parameters estimates combining the respondent's travel cost and choice experiment data. Note that, for the purposes of estimation, one of the quality-specific intercepts α_q has to be normalized to zero (in our case we set the “anything else” intercept to zero) and also that one of the $\alpha_{q,s}$ cannot be estimated (in our case we exclude α_{red} , and, therefore, the remaining parameters have to be interpreted as differences, i.e. as $\alpha_q - \alpha_{red}$) since the total quantity of water is the same in both options of the choice experiment.

To test the performance of our approach, we use Monte Carlo techniques to simulate the choices of a sample of respondents. Table 1 presents the ‘true’ parameter values selected for use in the simulation, these being chosen using a mixture of theoretical expectations, empirical regularities and simple common sense. Travel cost (TC) and choice experiment (CE) data are generated for different sample sizes distributed across the 100 most populated

UK Census Super Output Areas (SOA) as defined by UK National Statistics (2008) for the case study area. For simplicity, within the simulation exercise we assume that a respondent is asked either the TC or CE questions but not both, accepting that our proposed field design is far more efficient in that each respondent faces both sets of questions. Initially, we generate data for 4 TC and 6 CE respondents in each SOA (the CE simulation using both one design allowing for 6 choices per respondent and a second which doubled this number), delivering a sample of 1,000 respondents. Subsequently we halve this sample size and use various proportions of travel cost to choice experiment respondents.

Table 1: True parameter values in the Monte Carlo simulation

Parameter	True value	Definition
α	-1	distance parameter in the use value
α_{blue}	8	intercept in the use value for pristine (blue) quality
α_{green}	6	intercept in the use value for good (green) quality
α_{yellow}	4	intercept in the use value for fair (yellow) quality
α_{red}	2	intercept in the use value for poor (red) quality
α_{home}	1	intercept for staying at home (normalized to zero)
β_{blue}	6	Non-use value of a blue quality stretch
β_{green}	4	Non-use value of a green quality stretch
β_{yellow}	2	Non-use value of a yellow quality stretch
β_{red}	1	Non-use value of a red quality stretch (norm. to zero)
γ	0.5	Income and price parameter
δ	1.5	Scale parameter of the travel cost econometric error term
ϵ	2	Scale parameter of the structural error term in the use value of the choice experiment assuming that is a good proxy for the econometric error term.

For the purposes of the simulation exercise we assume that a recreational site exists at the midpoint of each of our nine river stretches and that respondents live at the centre of their respective SOA¹⁰. Applying this approach across our 100 SOAs generates a highly diverse, spatially distributed, array of sites and substitutes relative to the trip origin of each respondent. Distances from each potential trip outset origin to each of the sites were calculated using GIS techniques (Bateman *et al.*, 1999).

For each sample permutation 1000 Monte Carlo simulations were drawn with models being estimated using the “BFGS” optimization algorithm provided in the R statistical package (R Development Core Team, 2004). Parameter estimates resulting from the various sample definitions are reported in Table 2. We expect that the sample size, the number of choice experiments questions and the proportion of travel cost to choice experiment respondents to all be potentially influential determinants of the goodness of fit of the model. To examine these factors, in Table 2 we report some particularly significant simulations. Here column {1} reports estimated parameters from a sample of 1000 respondents generated from 6 CE and 4 TC respondents per SOA. Columns {2} and {3} reduce the sample size of 500, being 3 CE and 2 TC respondents per SOA. While columns {1} and {2} simulate 12 choices per CE respondent, column {3} reduces this to just 6 choices per CE respondent.

¹⁰ Such an approach has been shown to be a valid approximation of empirically observed distances (Bateman *et al.*, 1996). However, in our planned field trial this sampling strategy will be improved upon by considering the precise geographical distribution of respondents and recreational site (relaxing the assumption of perfect correspondence between stretches and sites). GIS techniques can typically identify home origin within a resolution of less than 100 metres within urban areas (somewhat larger in rural areas).

Table 2: Simulations results with different sample sizes

		{1}	{2}	{3}
Total sample size		1000	500	500
Respondents per SOA		6 CE 4 TC	3 CE 2 TC	3 CE 2 TC
No. of CE choices		12	12	6
Parameter estimate	True value			
α		-1.174	-1.354	-2.05
	-1	[-2.12; -1.01; -0.66]	[-3.39; -1.02; -0.60]	[-5.92; -1.37; -0.45]
α_{blue}	8	8.230	9.496	15.56
		[4.68; 7.03; 14.77]	[4.16; 7.10; 23.69]	[3.14; 9.68; 41.18]
α_{green}	6	5.870	6.787	11.16
		[3.34; 5.03; 10.50]	[2.93; 5.07; 16.58]	[2.17; 7.01; 30.3]
α_{yellow}	4	3.520	4.068	6.73
		[1.94; 3.02; 6.49]	[1.71; 3.07; 10.16]	[1.28; 4.15; 18.22]
α_{red}	2	1.126	1.292	2.08
		[0.24; 0.99; 2.35]	[-0.09; 1.00; 3.97]	[-0.02; 1.34; 6.68]
α_{home}	1	---	---	---
β_{blue}	6	4.986	5.051	6.51
		[4.13; 5.00; 5.83]	[3.50; 5.03; 6.31]	[2.59; 5.28; 13.99]
β_{green}	4	2.994	3.029	3.75
		[2.45; 3.00; 3.56]	[2.04; 3.03; 3.86]	[0.70; 2.89; 9.60]
β_{yellow}	2	1.008	1.030	1.50
		[0.68; 1.00; 1.55]	[0.51; 1.01; 1.55]	[0.26; 1.06; 3.92]
β_{red}	1	---	---	---
α	0.5	-0.496	-0.522	0.13
		[-0.74; -0.49; -0.27]	[-0.85; -0.51; -0.20]	[-1.52; -0.139; 3.08]
α	1.5	1.756	2.047	3.36
		[0.98; 1.51; 3.20]	[0.86; 1.54; 5.14]	[0.67; 2.11; 9.22]

δ	2	3.697 [0.68; 2.00; 9.77]	5.865 [0.47; 1.96; 26.45]	10.56 [0.08; 2.92; 48.16]
δ failed	1		16	185

Notes: Parameter estimates are reported as mean values from 1000 Monte Carlo simulation. Values in square brackets are 5%, 50% and 95% percentiles respectively.

Examining Table 2 shows, as expected, that increasing data availability reduces the number of times in which the maximization fails to converge (being this for convergence to a local maximum or to a discontinuity point). Furthermore, the means of the parameters of the non-linear part of the utility (the δ and α estimates) appear to be severely biased when the sample size is small (column {3}) and much closer to the real values for larger samples (columns 1 and 2). Note that the estimated parameter values do not correspond to the “true” values because we have normalized α_{home} and β_{red} , therefore, the estimated parameters in Table 2 have to be interpreted as differences with those two baselines. Interestingly, the median of the distribution seems to be a much better estimator than the mean for all sample sizes. The reason for this feature is clearly the non-normality of the distribution of the parameters, which, again becomes less marked when the sample size increases (e.g. Figure 2 and 3).

Figure 2: Kernel density estimates of the use parameter of good water quality (α_{green}).

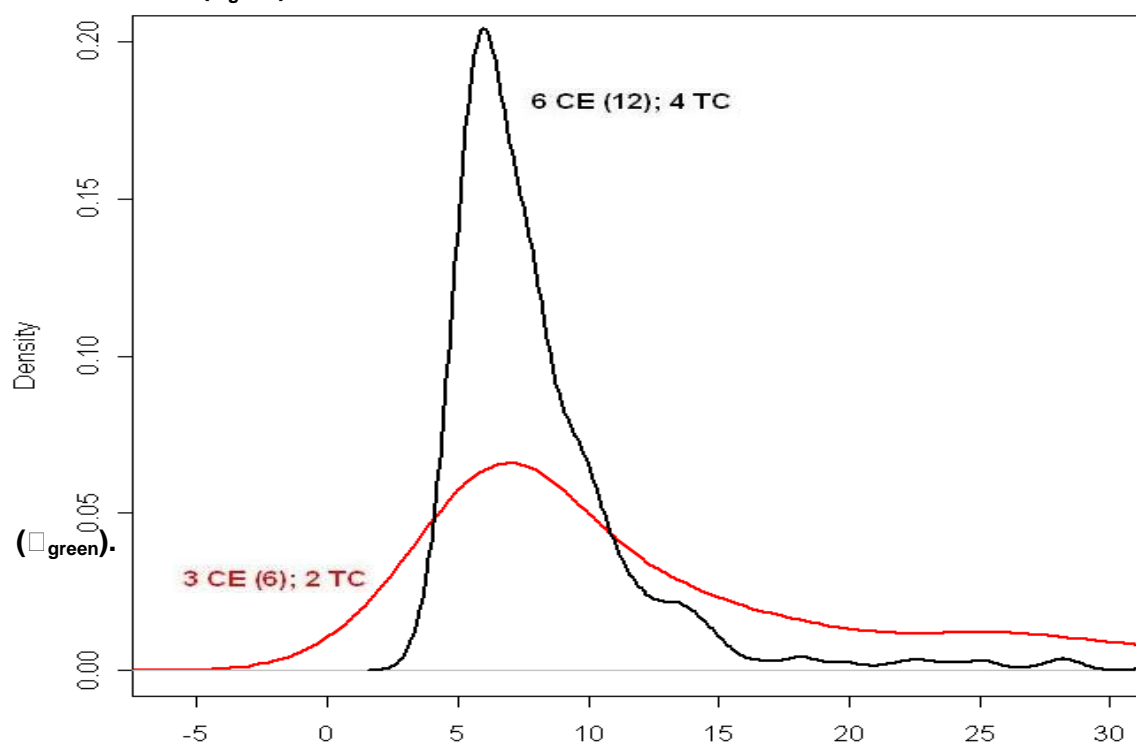
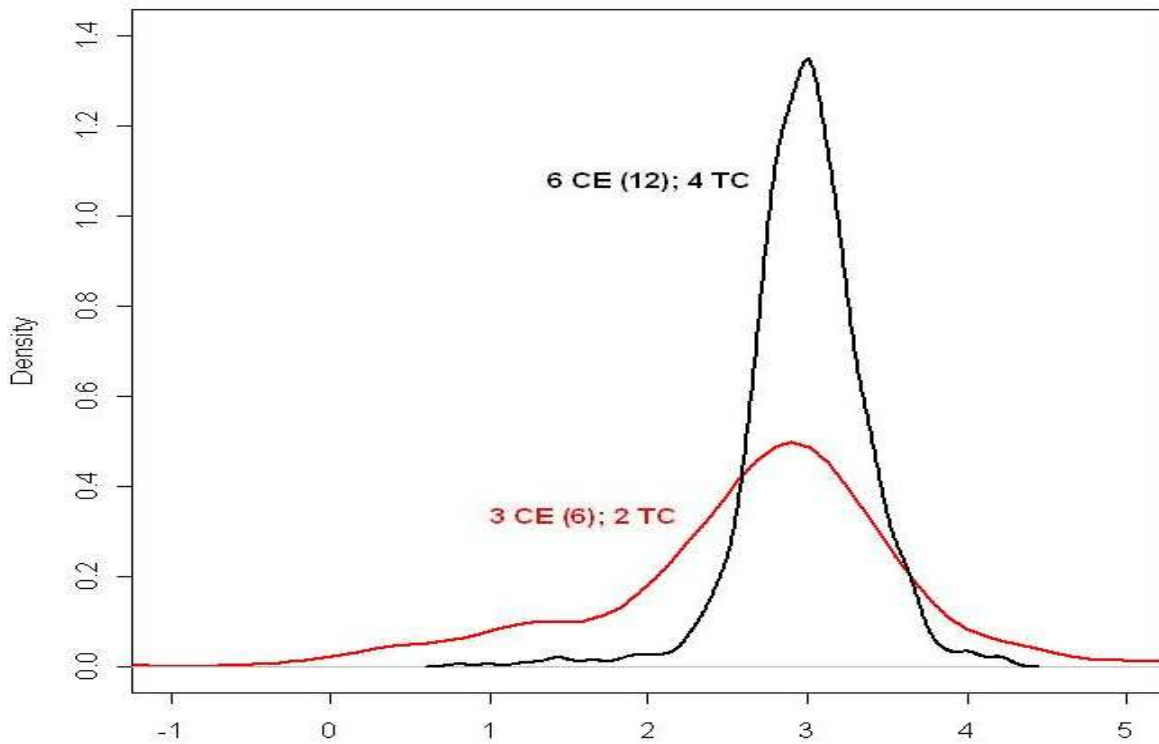


Figure 3: Kernel density estimates of the non-use parameter of good water quality



The parameters of the linear part of the utility (the β and γ estimates) can be estimated more precisely, however, a good amount of choices in the CE seems to be necessary to achieve good results (compare columns {2} and {3}).

Considering the complexity of the model, we can conclude that satisfactory results can be achieved with reasonable sample sizes. Recall that in our field trials each respondent provides both TC and CE data. Furthermore, recent piloting indicates that respondents can readily provide such data and answer 12 CE choice questions. Given this, a sample of just 300 respondents would be sufficient to generate results comparable to those given in column {2} of Table 2. Further enhancement of the precision of the model estimates could be delivered through an ongoing investigation of optimal sampling strategies.

5. CONCLUSIONS AND FINAL REMARKS

The identification of use and non-use values is crucial to policy and management decisions, guiding resource allocations among environmental conservation and other socially valuable activities. Traditionally, valuation methods identify either the use value or total value of a natural resource. Recent papers (Eom and Larson 2006, Haung *et al.*, 1997) address the problem of the identification and estimation of separate use and non-use values but impose

a variety of methodological restrictions upon the researcher, certain of which limit the representativeness of derived values. Similarly, much of the valuation literature (especially CE studies) typically ignores the availability and spatial distribution of sites and their substitutes. Further, the consumer behaviour has been normally assumed deterministic but we advocate the existence of uncertainty that should be considered in the random utility model formulation.

The methodology proposed in this paper combines travel cost and choice experiment data to distinguish use and non-use values of a natural resource within a random utility framework. Our approach is attribute-based, thereby allowing estimation of the contribution of each attribute to use and non-use derived utility. Furthermore, it allows us to handle situations where the environmental changes exhibit complex geographical patterns impacting on numerous locations some of which are used for recreational purposes and some not, since include and separately estimate both use and non use.

The performance of the model is tested in a simulation exercise examining the non-market benefits which may arise from implementation of the EU Water Framework Directive. The travel cost and choice experiment aspects of the study are defined as per our planned field application and the respondents' choices are simulated via a Monte Carlo experiment. Results show that, even in the complex case of a non-linear utility function in which the likelihood might not be globally concave, the use and non-use parameters can be precisely estimated via standard ML techniques based upon a modest sample of observations. Given the (to date) largely unsupported emphasis accorded to non-use values within some policy decisions and the lack of explicit incorporation of spatial complexity within valuation studies, we believe that the approach proposed in this study can give important insights in improving the economic assessment process.

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