Expanding Stated Preferences: Augmenting Choice Experiments with Contingent Behaviour Data in the Demand for Recreation

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Abstract

In valuing the demand for recreation, the literature has grown from using revealed preference methods to applying stated preference methods, namely contingent valuation and choice modelling. Recent attempts have merged revealed and stated preference data to exploit the strengths of both sources of data. In this paper we expand the strength of merging revealed and stated preferences by combining three sources of data to improve the valuation of the demand for recreation. We merge revealed preferences from a travel cost study (TCM), contingent behaviour (CB) and choice experiments (CE) to assess whether the decisions on the expected number of trips to a recreational site have any effect on respondents' preferences for hypothetical management programs of the recreational area. We find that Choice Experiments that investigate which attributes of a site are preferred by respondents, but do not consider the expected number of trips to the site under the hypothetical scenarios offered to respondents, provide biased estimates. By considering the expected number of trips under different scenarios, our approach is better able to disentangle use and non-use values.

Keywords: travel cost, contingent behaviour, choice experiments, revealed preferences, stated preferences

JEL: Q51, Q26

1. Introduction

In valuing the demand for recreation, the literature has grown from using Revealed Preference (RP) methods (Clawson & Knetsch, 1966; Bhat, 2003; Bhat & Gossen, 2004) that are only able to assess use values of a recreational site to applying Stated

Preference (SP) methods, namely contingent valuation (CV) (Bateman et al, 1994) and choice modelling (CM) (Louviere and Timmermans, 1990) that in addition to use values, are able to capture non-use values. Both approaches have been criticized for their respective limitations: RP methods can only assess use values; while SP methods are based on hypothetical scenarios. To overcome the shortcomings of each method, recent attempts have merged the two in order to exploit the strengths of both sources of data (Adamowicz et al, 1994, 1997, 1998; Alberini and Longo 2006; Alberini et al 2007; Cameron, 1992; Cameron et al, 1996; Christie et al 2007; Englin and Cameron 1996; Eom and Larson, 2006; Hanley et al 2003; Huang et al 1997; Whitehead et al 2000, 2005, 2007, 2008 and Bhat 2003). A number of these studies have been summarised and discussed below to give an indication as to how they have been applied to different research topics and scenarios.

Bhat (2003) combines the Travel Cost Method (TCM) and Contingent Behaviour (CB) and applies them to the non-market recreational benefits of reef quality improvements in the Florida Keys. Data was collected using a sample of visitors to the Keys to ascertain their revealed travel preferences to the site, under current conditions, and to give an indication about their future travel preferences. A panel recreational demand model was applied to the collected data for current and expected quality scenarios to allow for an estimation of the benefits related to the quality improvements of the reefs. A Poisson regression model was used to capture the variation in responses across the respondents. The eventual travel cost per person was calculated by multiplying the total round trip distance by a per mile group trip costs. It was estimated that the average person took 6.31 trips to the Florida Keys over the period of 5 years primarily for the purposes of diving, snorkelling and / or glass bottom boat riding under the current environmental conditions. The use values for these trips were estimated to be a cost of $2924 per person, $463 per person trip, and a daily cost of $122 per person (Bhat 2003). Under future environmental improvements, it was estimated that for the improvements in the attributes, fish abundance (200%), water visibility (100%) and coral quality (100%), an average visitor would make 4.99, 3.88 and 2.70 more trips respectively during the five year period (Bhat 2003).

Eom and Larson (2006) apply information obtained from a study incorporating elements of RP and SP techniques to improving environmental valuations in the Man Kyoung River (MKR) basin in South Korea. Their research provides a framework for estimating use, non use and the total values of changes to environmental quality by combining the TCM as their RP component with CV as their SP component (Eom & Larson 2006). Their results show that most of the explanatory variables impacted on the trip demands and the willingness to pay (WTP) functions, with the correct signs. The travel cost had significant influence on the number of visits to a typical site and affected the likelihood of a respondent being willing to pay a given bid amount. Full income was shown to have a positive effect on demand and WTP. Water quality was significant in both decisions. Annual total WTP to restore the current level of water quality to a level acceptable for fishing was $26.56, made up of $16.35 for the use value and $10.21 for the non use values. These were significantly different to zero at the 95% confidence interval. For water quality to return to a swimmable level, WTP was $47.64 split into $29.78 for use values and $17.86 for non use values, all of which were again significant (Eom & Larson 2006).

Huang et al (1997) sought to combine RP and SP in order to estimate WTP for quality improvements in North Carolina where two recreational sites were identified (one of which was a component of the other). They wished to identify and show the conditions required in order to continuously combine RP and SP data in order to return an improvement in environmental quality. A joint estimation was proposed to provide an estimate of both the variation function model and for the change in the level of recreational demand. A regression model was used with a recreation demand model to determine whether the data obtained from the CB questions matched what was theoretically anticipated. Negative binomial models were used as well as a trip change model. The variation function model was also estimated for both the single and the double bounded CV data (Huang et al 1997).

Results obtained matched their hypothesis; respondents fully considered the difference between the ex-ante trips under the present conditions with the quality improvement rather than the difference between the ex-post and the ex-ante number of trips under improved quality conditions. They highlight that there may be an inconsistency when current recreation demand and dichotomous WTP responses are jointly estimated when it is assumed that the underlying preference structure to be the same (Huang et al 1997).

Whitehead has written much in the way of merging valuation methods (Whitehead et al 2000, 2005, 2007 and 2008) with a number of difference co-authors. Whitehead et al (2000) propose that by merging RP and SP behaviour they can produce an estimation method to measure recreational benefits that could come from a quality improvement. They apply the TCM and CB to a 1995 telephone study of eastern Californian households to test attitudes towards a proposed management plan. A random effects Poisson model was used with dummy variables in order to consider the heterogeneity amongst the individuals within the sample. The RP and SP behaviour models which have the same quality levels were tested to see whether they represent the same underlying behaviour of the respondents. Their results have indicated that both a shift and a change in the elasticities of recreation demand as well as the environmental quality are improved. Whitehead et al (2000) conclude that both RP and SP behaviour data can be combined, once any hypothetical bias has been calibrated within the data, implying that they represent the same underlying behaviour of respondents at the current levels the environmental quality (Whitehead et al 2000).

Whitehead (2005) combines CV and TCM and uses it to evaluate the benefits of improved water quality in the Neuse River in North Carolina. Tobit models were utilised for the analysis and for all three models undertaken, the WTP estimate is approximately $75. The demand change result highlights that the more frequent visitors of the Neuse River are willing to pay more, while the WTP estimates of respondents in the Upper river basin are greater than those in the lower river basin. WTP is reduced where respondents perceive the water in the river to be unsafe, which is contradictory to the expected sign. Concluding remarks further suggest that empirical models of WTP should seek to ensure that exogenous measures of the potential use of the resource being measured should be included and that future CV research should explore and identify alternative approaches to merging WTP and behaviour data, which will further validate the CV method (Whitehead 2005).

Whitehead et al (2007) provide an in depth analysis of combining RP and SP data and discuss a number of ways they can be merged, including the advantages and disadvantages from combining such data and the models employed to analyse the combination of valuation techniques. Conclusions include that by merging RP and SP data, the advantages of both types of data can be fully utilised whilst mitigating again their weaknesses. An increased level of estimation efficiency is also obtained when the two are merged successfully (Whitehead et al 2007).

Whitehead et al (2008) illustrate how combining RP (TCM) and SP (CB) was applied to North Carolina beaches in order to estimate changes in recreational demand. A random effects Poisson model was used to estimate three recreation demand models.

Hypothetical bias was found across the three models owing to the number of SP trips far exceeding the number of RP trips specified by respondents under comparable conditions giving them similar benefits. In conclusion, Whitehead et al (2008) state that they outlined a number of ways by which hypothetical bias from the CB can result in an overestimation of the economic benefits of recreation and those that come about as a result of environmental improvements to the baseline / status quo situation. Through their analysis, it was shown that the hypothetical bias affected the estimates obtained for the number of trips and the regression coefficients (Whitehead et al 2008).

Hanley et al (2003) value the benefits of coastal water quality improvement by applying contingent and real behaviour. They apply a random effects negative binomial panel model with data from real and contingent behaviour and enables them to predict a change in trip numbers should the level of water quality be improved. The Poisson and the negative binomial models were utilised and show that travel costs have a negative influence on the number of trips undertaken to a site by respondents. The coefficient on the level of water quality was negative and significant while the effect of the individual on their willingness to swim is positive and significant. The negative binomial model shows that across the entire sample, an increase of 52 trips is predicted as a consequence of an improvement in the level of water quality within the area. By combining the SP and RP information, it was possible to undertake a panel data approach, and suggested that the hypothetical improvements in water quality showed an increase of 1.3% in the predicted trip frequency to the sites. The use of CB enabled Hanley et al (2003) to investigate the value any improvements to the water quality would result in (Hanley et al 2003).

Christie et al (2007) looked at valuing forest recreation using choice experiments and contingent behaviour in order to value a range of improvements to recreational facilities in forest and woodlands in Great Britain (GB). This research uses both Choice experiments and contingent behaviour allowing for a direct comparison of the benefit estimates obtained from the data. Data was collected through in person interviews between May and September 2005 and seven forests throughout Great Britain chosen for their ability to cover the range of activities being investigated. Respondents were presented with some background information on the study and asked to specify how they used the forests for recreation. They were then presented with information on how the forest they were in could be improved before being shown a single CB scenario. From this, they were asked to outline whether their intended trips to this forest would change within the next 12 months should these improvements be implemented. They were then given a series of four CE choice tasks. Results suggest that within the CB models, the consumer surplus estimates can be influenced by the consumer surplus values per visitor, as well as the forecasted changed in the number of recreational visits they might make, whereas, within the CE model, only the estimates of consumer surplus values per trip are taken into account (Christie et al 2007).

2. Approach

In this paper we expand the strength of merging revealed and stated preferences data by combining three sources of data to improve the valuation of the demand for recreation. In the demand for recreation to the Mournes Mountains in Northern Ireland, UK, we merge revealed preferences from a travel cost study, contingent behaviour (CB) and choice experiments (CE) to assess whether the decisions on the expected number of trips to a recreational site have any effect on respondents' preferences for hypothetical management programs of the mountain area.

We start from a single site travel cost survey, where respondents provide us with welfare estimated for the access value to the recreational area. This is the use value of respondents for the recreational area. Following Whitehead et al (2000), we further query respondents with a set of CB questions about their expected number of trips to the site in the next 12 months under the current situation, and under different scenarios. These scenarios are described by the *levels* of the attributes later used in the CE. The final part of the valuation exercises presents a set of CE questions used to assess both use and non use values of the recreational area. A usual limitation of the CE questions in the context of eliciting the WTP for a recreational area is offering respondents with scenarios including the expected number of trips that respondents would undertake under each scenario. If the enumerator presents respondents with hypothetical expected number of trips that the respondents is supposed to take to the site in the next season, the respondent may well protest the survey. To overcome this problem, when we analyse the data from the choice experiments, we use the responses from the CB data on the number of days that respondents expect to take to the site under the hypothetical scenarios to augment the CE data. In this way we are able to identify whether an important missing *subjective* attribute, namely the expected number of trips under hypothetical scenarios, play any role in respondents' answers to CE questions. In addition, we are better able to assess how *use values* components affect CE answers. Formally, in our CB model we have:

$$(1)\quad TRIPS_{n\,j}=\gamma Z_{nj}+\mu$$

Where $TRIPS_{nj}$ is the number of expected trips that respondent n takes under scenario j for the CB questions; Z is a vector of explanatory variables including scenarios levels (excluding the cost of that scenario in the CE questions, but including the travel cost); μ is the error term and γ is a vector of parameters to be estimated. Later we show respondents CE questions built with the same levels used in the CB questions, plus the cost (in form of an annual tax) for each scenario. Under the Random Utility Model framework (Luce 1959, McFadden 1973) we assume that a respondent selects the hypothetical management program of the Mournes Mountains that gives him/her the highest level of utility. Formally, respondent n will choose alternative j, if the utility from alternative j is higher than the utility from the other alternatives in choice set A:

$$(2)\quad \Pr(n \text{ chooses } j)=\Pr(V(x_{nj})+\varepsilon(x_{nj})>V(x_{ni})+\varepsilon(x_{ni}),\ \forall j\neq i\in A)$$

The vector X includes the same variables (levels) used in the CB questions, excluding the travel cost, but including the cost (tax) for each alternative. Using likelihood ratio tests we investigate whether respondents do consider their expected number of trips associated when choosing hypothetical scenarios in the choice experiments questions. Our results highlight how to consider *use values* components when using stated preference methods for valuing the protection of natural areas where a recreational component may be important for the welfare of respondents.

3. The case study and the survey instrument

Northern Ireland is the only administrative division within the United Kingdom that does not have a National Park. The idea for a National Park in Northern Ireland was first raised by the Planning Advisory Board in their 1946 report "The Ulster Countryside" (Northern Ireland Planning Advisory Board 1947). It identified the Mourne Mountains in particular and requested its immediate designation. The Mournes area is one of the most striking mountain districts in Ireland. It comprises twelve peaks each rising above 600m (1968.5 feet). Much of the area is included within the Mourne Area of Outstanding Natural Beauty (AONB) in recognition of the quality of its landscape. The area boasts the first National Nature Reserve to be designated in Ireland and has an abundance of pure water reserves within its 9,000-acre catchment area demarcated by the 22-mile long Mourne Wall, which supplies the local Mournes area and much of Belfast (Kirk 2002).

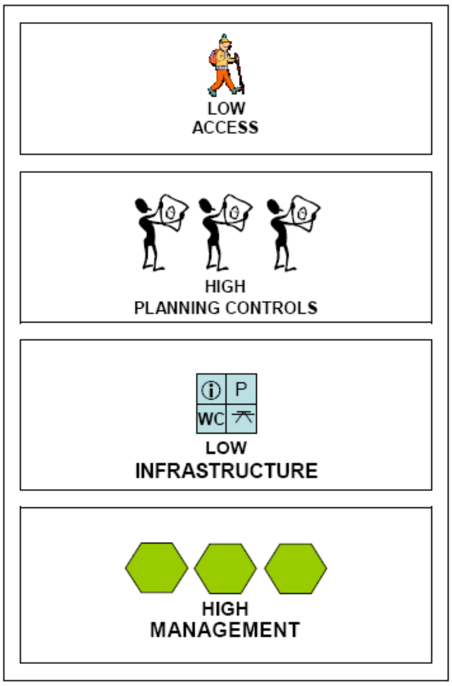
In September 2002, the Minister for the Environment expressed a commitment to progress towards a Mourne National Park provided there was sufficient public support for such a designation. A study in 2002 identified the Mournes area as being the place most suited to a National Park designation and becoming Northern Ireland's first National Park (Europarc 2002). The Mourne National Park Working Party (MNPWP) was established in 2004 by government as an independent body whose role was to commission research on a National Park boundary and to investigate the prospect of National Park designation for the Mournes area (EHS NI 2004). The MNPWP undertook an extensive public consultation exercise within the Mournes area which ran from August 2006 through until January 2007 (Inform Communications 2007) with their final report highlighting that residents of Northern Ireland deem important the following attributes for a Mournes National Park: (i) access to the area, (ii) infrastructures at the area, (iii) planning restrictions a the area, (iv) the type of management of the site. Following the results from the extensive public consultation carried out by the MNPWP, for this survey we use these four key attributes as attributes for the CE and for describing the hypothetical scenarios in the CB questions. We set these attributes at two different levels – high and low (being the status quo too). The attributes therefore are *infrastructure* (toilets, parking facilities, rest spots availability, visitor centre and information provision), *access* (onto public and private lands), *planning* restrictions (controls for design of buildings and materials used), the type of *management* for the area as well as a *cost* attribute. These attributes are represented by symbols and have been clearly set out in the survey instrument. For the CE part of the survey, a *cost* attribute is be presented to each respondent in each of the options given in the choice sets. The payment vehicle devised is an annual environmental tax to be collected from all wages, salaries, pensions and social security payments. The maximum and minimum amounts people were willing to pay for the alternatives presented to them were determined through the focus groups, and set at 5 levels (£2, £6, £10, £15 and £25). We create the experimental design following Johnson et al (2007) using SAS 9.1. Respondents are presented with four CB questions and 4 CE questions. Each CE question presents two hypothetical scenarios and the status quo option. The four CB questions are built using the same levels used in the second and third CE questions, except for the tax that does not appear in the CB questions. Figures 1 and 2 present the scenarios used for the first CB question and for the second CE question in one of the questionnaires. The reader can notice that the first alternative in the CE question is described with the same levels used for the CB question. The survey instrument was administered by mail after the summer of 2008 to a sample of the population of Northern Ireland.

Figure 1. Example of CB question

PART 3: Consider your next trips to the Mournes area

The following questions ask you to choose how many times you would visit the Mournes area within the **next 12 months** period if these particular programmes were implemented.

1. Would you visit the Mournes area if the following were to be implemented?



Yes ☐ No ☐ Don't know ☐

If you have answered "Yes", how many days would you visit the Mournes area in a 12 month period?

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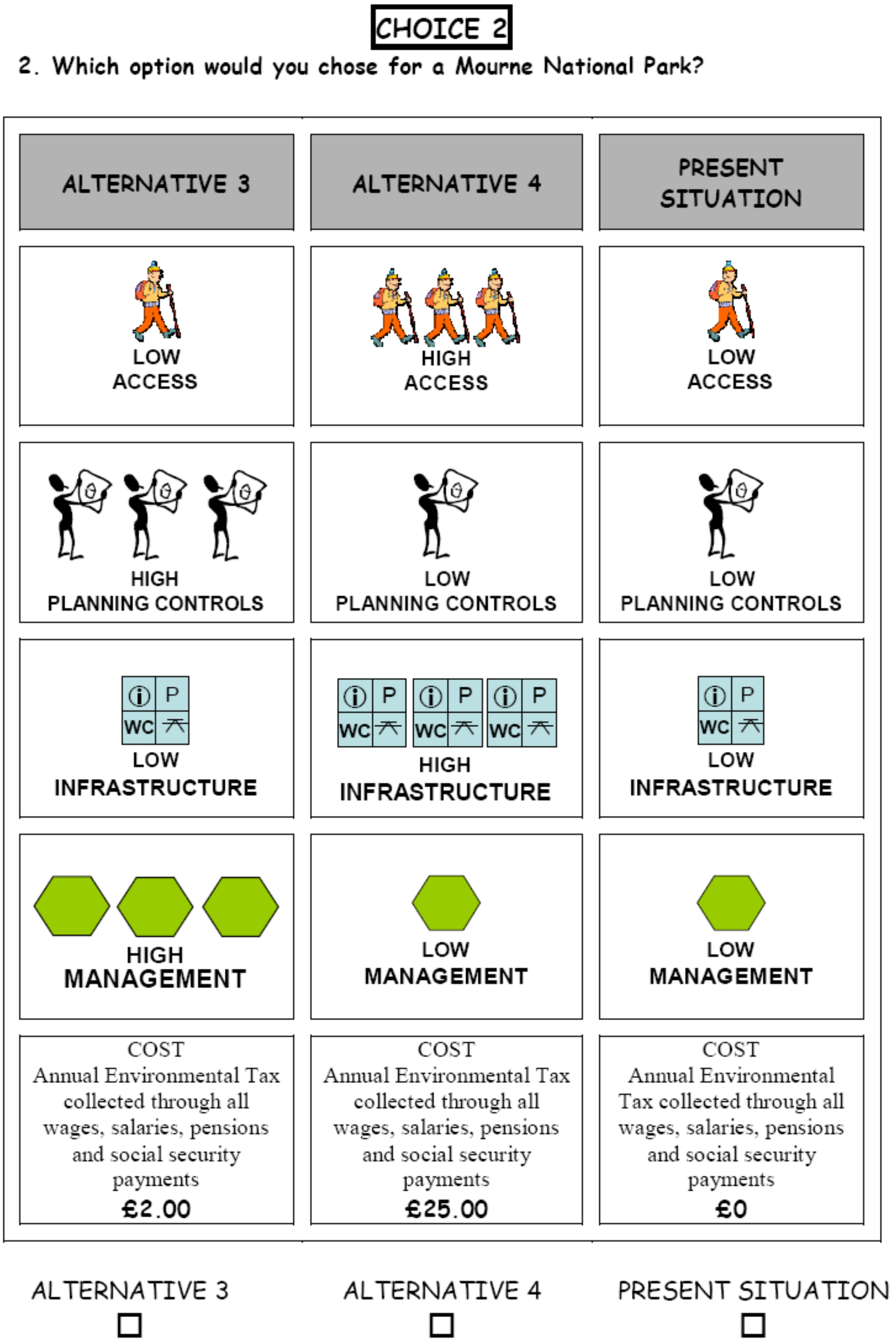
Figure 2. Example of CE question.



4. Econometric approaches

In a single-site travel cost method (TCM) model, it is assumed that an individual's utility depends on aggregate consumption, *X*, leisure, *L* and trips *r* to the site:

(3) $$U = U(X, L, r).$$

We further assume weak complementarity of trips with quality at the site, *q*. In other words, $\partial U / \partial q = 0$ when *r* = 0 (when a person does not visit the site, his or her utility is not affected by its quality), and *r* is increasing in *q*. The individual chooses *X*, *L* and *r* to maximize utility subject to the budget constraint:

(4) $$y + w \cdot \left[\overline{T} - L - r(t_1 + t_2)\right] = X + \left(f + P_d \cdot d\right) \cdot r$$

where *y* is non-work income, *w* is the wage rate, $\overline{T}$ is total time, t_1 is travel time to the site, t_2 is time spent at the site, *f* is the access fee (if any), P_d is the cost per mile, and *d* is the distance to the site. This yields the demand function for days:

(5) $$r^* = r^*\left(y, w, p_r, q\right)$$

where $p_r = w(t_1 + t_2) + f + p_d \cdot d$ is the full price of a trip.

In this study, we assume that the demand function is log linear. Formally,

(6) $$r^* = \exp(\beta_0 + \beta_1 w + \beta_2 p_r + \beta_3 q).$$

In our econometric model below, r^* is the expected number of trips. To estimate the coefficients in equation (4), it is necessary to ask a sample of visitors to report the number of trips they took in a specified period (year or season), cost per trip p_r, plus *w*, *y*, and other individual characteristics that might affect the demand for visits to the site.

Since *q*—the quality of the site—does not change over time, to estimate the coefficient on *q*, β_3, we devised a set of CB questions that would deliver specific improvements at *q*, and asked our respondents to tell us how many days they would spend if the program was implemented under alternative assumptions for *q*. Once the demand function has been estimated, the consumer surplus provides an approximation of the welfare associated with visiting the site. Formally, based on equation (6), the consumer surplus is equal to:

(7) $$CS(p_0, q_0) = -\frac{1}{\beta_2} r_0,$$

Where r_0 is the predicted number of trips from the model.

Given the relatively few annual trips to the site, a count data model is the appropriate model for the number of trips Y. We specify a Poisson model with individual-specific λ_{ij}:

(8) $$\Pr(Y_{ij} = y_{ij}) = \frac{e^{-\lambda_{ij}} \lambda_i^{y_{ij}}}{y_{ij}!},$$

where $\lambda > 0$ is the parameter of the Poisson distribution (which is equal to both the expected value and the variance of Y_{ij}), $\lambda_{ij} = \exp(\mathbf{x}_{ij}\boldsymbol{\beta}_1 + p_{ij}\beta_2 + q_j\beta_3)$, **x** is a vector of determinants of visits to the Mournes, p_{ij} is the price per trip faced by the respondent, and q_j is a vector of four dummies capturing the presence/absence of improvements to access, infrastructure, planning policies, management of the site. $\boldsymbol{\beta}_1$, β_2 and β_3 are unknown coefficients. The subscripts i and j denote the respondent (i=1, 2, …, n) and the scenario within the respondent, respectively (j=1, 2, 3, 4, 5 where j=1 refers the current conditions, and j=2, 3, 4, 5 refer to the scenarios with the hypothetical CB questions. The vector **x** includes the total cost of the trip to the Mournes and to a substitute site (the Sperrins mountains) as reported by the respondent, including the cost of time, divided by the number of people for whom this cost was incurred.

To capture the panel structure of our dataset when considering the CB answers, we use a random effects Poisson model.

Our statistical analysis of the responses to the CE questions is based on the random utility model (RUM), which assumes that respondent's indirect utility is broken down into two components. The first component is deterministic, and is a function of the attributes of alternatives, and a set of unknown parameters, while the second component is an error term (McFadden, 1974). Formally,

(9) $$V_{ik} = \overline{V}(\mathbf{x}_{ik}, \boldsymbol{\beta}) + \varepsilon_{ik}$$

where the subscript i denotes the respondent, the subscript k denotes the alternative, **x** is a 1×5 vector comprised of the five attributes: the annual tax, the level of access, the level of the infrastructures, the level of management of the national park, the level of planning constraints, $\boldsymbol{\beta}$ is a vector of unknown coefficients and ε is an error term that captures individual- and alternative-specific factors that influence utility, but are not observable to the researcher. We further assume that the indirect utility function is linear in parameters:

(10) $V_{ik} = \beta_{0k} + \mathbf{x}_{ik}\boldsymbol{\beta} + \varepsilon_{ik}$,

We further posit that in each of the choice questions the respondent selects the alternative with the highest indirect utility:

(11) $\pi_{ik} = \Pr(V_{ik} > V_{i1}, V_{ik} > V_{i2}, ..., V_{ik} > V_{iK}) = \Pr(V_{ik} > V_{ij}) \quad \forall j \neq k$

where π_{ik} signifies the probability that option k is chosen by individual i. If the error terms ε are independent and identically distributed and follow the type I extreme value distribution, the probability that the hypothetical policy k is selected out of K policies is:

(12) $\Pi_{ik} = \Pr(resp.\ i\ chooses\ k) = \exp(\mu V_{ik}) \Big/ \sum_{j=1}^{K} \exp(\mu V_{ij})$,

where μ is the scale parameter which is inversely proportional to the standard deviation of the error terms. Equation (12) is the contribution to the likelihood in a conditional logit model. In our questionnaire, K=3. The log likelihood function of the conditional logit model is:

(13) $\ln L = \sum_{i=1}^{n} \sum_{k=1}^{K} y_{ik} \cdot \ln \pi_{ik}$,

where y_{ik} takes on a value of 1 if the respondent chooses k, 0 otherwise. The coefficients are estimated using a Maximum Likelihood Estimation Method. The model described by (12) and (13) allows us to estimate the trade off between any two attributes and the willingness to pay for different policies. The marginal price of attribute k is given by:

(14) $MP_k = -\frac{\hat{\beta}_k}{\hat{\beta}_c}$,

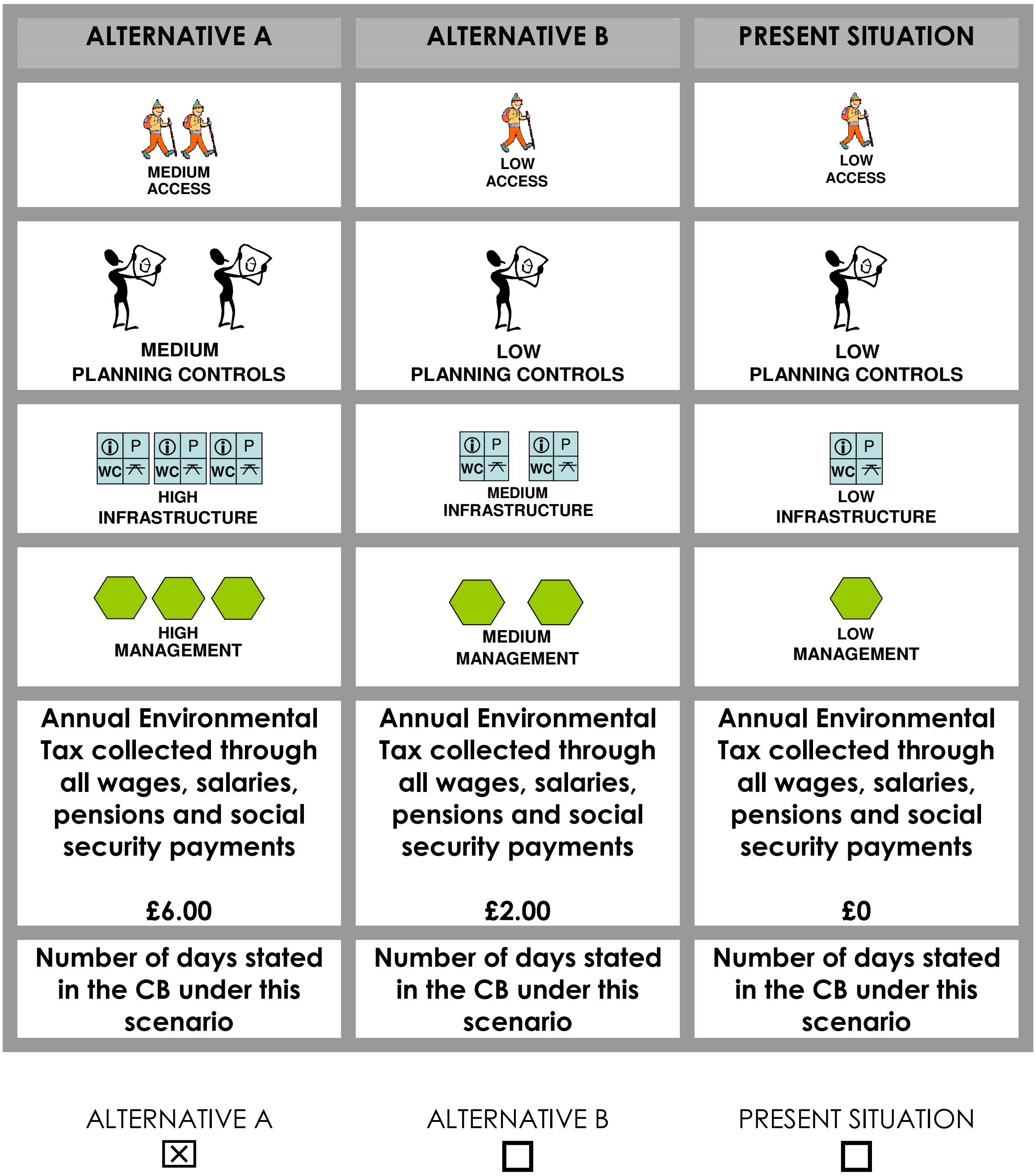
where $\hat{\beta}_k$ is the utility from an extra unit of k. Divided by the price coefficient, $\hat{\beta}_c$, it gives us the monetary value of the utility coming from an extra unit of k. Finally we can derive the willingness to pay for a certain policy, formally:

(15) $WTP_{ik} = -\frac{x_{ik}\hat{\beta}}{\hat{\beta}_c}$

Where x is the vector of the levels of attributes of program k given to individual i.

When we merge CB and CE in equation (9) the vector **x** becomes a 1×6 vector comprised of the five attributes previously described plus the number of days at the Mournes in the next 12 months under the hypothetical scenarios presented to the respondents. This number of days is taken from the answers that the respondent had previously given in the CB questions. An example of how we would expect this to look within a choice set is shown below.

Figure 3. Example of CE augmented with CB question



5. Results

Of the 4,507 surveys sent, we received 647 questionnaires back, for a response rate of 14.36%. On average respondents had spent 2.49 days to the Mournes mountains in the last 12 months. When asked how many days they would spend in the next 12 months at the current condition, they claimed to be willing to spend 5.07 days. This result is consistent with previous studies that found that respondents may overestimate the number of days they are willing to spend at a recreational site in the future under the status quo situation (Whitehead et al, 2000). Therefore, in the CB model, when we assess how changes in the levels of infrastructures, access, planning controls and management to the area affect the number of expected days compared to the current situation, we use the expected number of days that respondents expect to spend at the Mournes in the next 12 months and not the number of days they spent in the past 12 months.

Results from the Poisson (Model 1) and the Negative Binomial (Model 2) models from the travel cost model based on the trips spent in the past 12 months are reported in Table 1. The estimated coefficients have the expected signs and are statistically significant, with the coefficient for the travel cost to the Mournes being negative and the coefficient to the substitute site (the Sperrins) being positive. This signifies that as the cost to the Mournes increases, the number of trips being made there is reduced. However, as the cost for individuals to travel to the Sperrins increases, the number of trips to the Mournes as a substitute site increases. This is not the same for the Glens, suggesting that is does not act as a substitute site for either the Mournes or the Sperrins. From this basic Poisson model (1) we can calculate the welfare associated with visiting the Mournes, which is equal to £39.93 per year. However, given the nature of the Alpha statistic reported from the Negative Binomial (model 2), being both positive and significant, we conclude that this model best describes our data. The coefficients for the cost attribute are the same as for the Poisson (negative for the Mournes, as expected, and positive for the Sperrins), but are slightly larger. The access values derived from the Negative Binomial are £25.06 per year. The dependent variable was the number of days respondents had spent in the Mournes within the previous 12 months.

Table 1. Travel cost model. Poisson model. Dependent variable is number of days at the Mournes in the last 12 months.

Travel Cost	Poisson Model (1)		Negative Binomial Model (2)	
	Coeff	t-stat	Coeff	t-stat
Constant	0.3580	11.12	0.1785	0.54
COST_Mournes	-0.0529	-8.67	-0.1411	-2.81
COST_Sperrins	0.0848	9.02	0.2067	2.56
COST_Glens	-0.0298	-3.27	-0.0627	-0.69
Alpha			12.8190	8.85
Observations	647		647	
Log likelihood function	-2639.485		-749.9583	
WTP	£39.93		£25.06	

In Table 2, we report the outcome from two models that augment the travel cost model with the CB questions. Model (3) is a Poisson model, while Model (4) shows the Negative Binomial model for the same data. The coefficients of model (3) have the expected signs and are statistically significant (except for the cost to the Sperrins), with access being the most important attribute, followed by infrastructures, planning and finally management. Model (4) shows a different set of results for the attributes, with infrastructure ranking as the most important, followed by access, management and finally planning. Infrastructure is significant at the 10% level with a t-stat of 1.76. As was the case with the previous Negative Binomial model (2), the Alpha statistic in model (4) is positive and significant, again, suggesting that this best suits the nature of our data.

Table 2. Contingent behaviour model. Poisson model and Negative Binomial model. Dependent variable is number of days at the Mournes in the next 12 months under the current condition, improved infrastructure, access, planning and management.

Contingent Behaviour	Poisson Model (3)		Negative Binomial Model (4)	
	Coeff	t-stat	Coeff	t-stat
Constant	1.3330	44.70	1.2878	12.08
COST_Mournes	-0.0717	-38.42	-0.0979	-17.19
COST_Sperrins	0.0663	2.59	0.0832	10.59
INFRASTRUCTURE	0.0902	4.23	0.1149	1.76
ACCESS	0.0988	4.38	0.1039	1.39
PLANNING	0.0410	2.06	0.0445	0.67
MANAGEMENT	0.0267	1.45	0.0480	0.85
Alpha			1.6741	32.35
Observations	2588		2588	
Log likelihood function	-13917.66		-6838.074	

Table 3 reports the results of the conditional logit models for the CE questions. Model (5) is the basic model with a status quo, capturing the effect of respondents choosing the current situation, while model (6) shows results of an augmented MNL model with the variable DAYS that describes the number of days that respondents are willing to spend at the Mournes under the different scenarios described in the CB questions. DAYS is both positive and significant suggesting that respondents do consider this *subjective* variable when making their choice between hypothetical scenarios presented to them in the choice sets. As with our previous model, this model also produces coefficients estimated with the expected sign and are statistically significant. The order of importance of the coefficients has changed again compared to the contingent behaviour models. While infrastructure is again the most important attribute, management of the site is ranked second, followed by planning and finally by access levels. A likelihood ratio test shows that model (6) outperforms model (5). This suggests that when respondents answered the CE questions, they indeed considered the expected number of trips they would undertake to the Mournes under the specified hypothetical programs. Therefore, not considering the number of days would result in biased coefficient estimates, as in Model (5). The variable DAYS well captures the use value component of the total economic value of the Mournes National Park.

Table 3. Choice experiments models: Conditional logit models

Choice Experiments	Attributes only model (5)		Attributes augmented with number of visits model (6)	
	Coeff	t-stat	Coeff	t-stat
STATUSQUO	0.4844	4.47	0.4985	4.59
ACCESS	0.3800	5.85	0.3726	5.73
PLANNING	0.4693	7.77	0.4685	7.74
INFRASTRUCTURE	0.7875	10.60	0.7855	10.57
MANAGEMENT	0.4701	7.97	0.4728	8.00
COST	-0.0475	-10.78	-0.0480	-10.88
DAYS			0.0620	3.30
Observations	2129		2129	
Log likelihood function	-2196.829		-2190.246	

Table 4 shows a further analysis of Model 6 whereby access values have been calculated, first on the CE data, and after, augmenting it with the CB data obtained. As can be seen, results which do not consider the expected number of days a respondent will travel to the Mournes in the next 12 months (under the hypothetical CB scenarios presented to them) results in lower WTP estimates and t-stats, again suggesting biased coefficient and WTP estimates. By including the expected number of days a respondent will visit gives marginally higher WTP estimates and t stats. These results show non use values only, as well as use values for one day and for the mean number of days (3.5 is the sample mean found through the Negative Binomial in the TCM). Results below for one day trip to the Mournes shows that, depending on the scenario implemented, respondents have an access value of between £3 - £12, while for the mean number of days, access value range from £48 - £110.

Table 4. Access values for the Mournes captured through WTP estimates for the Choice Experiment, Conditional Logit Models

Choice Experiments	WTP Non use values only		MNL Model (6) WTP Non use and use values for 1 day		WTP non use and use values for average respondent going 3.5 days to the Mournes	
	WTP (£)	t-stat	WTP (£)	t-stat	WTP (£)	t-stat
High access, Planning, Infrastructure, Management	40.06	10.83	43.07	10.90	152.31	10.91
High access, Planning, Infrastructure, Low management	34.50	10.67	38.35	10.85	135.62	10.85
High Access, Planning, Low Infrastructure, management	23.21	10.15	29.45	10.75	104.15	10.75
High Access, Low Planning, Infrastructure, Management	7.76	5.33	19.21	10.41	67.94	10.42
High Planning, Low Access, Infrastructure, Management	9.76	6.45	20.38	10.25	72.09	10.25
High Infrastructure, Low Access, Planning and Management	16.36	7.99	24.59	10.29	86.97	10.29
High Management, Low Access, Planning and Infrastructure	9.84	6.57	20.44	10.26	72.28	10.25

6. Conclusions

This paper has investigated whether CE used to assess the WTP for improvements at recreational sites suffer from the problem of considering the number of trips to the site under hypothetical scenarios. Asking respondents to trade off hypothetical programs where the researcher inputs the expected number of trips to a site may not be credible by the respondent. Previous studies have cleverly attempt to circumvent this problem by asking respondents to allocate the next *y* number of trips to the hypothetical programs (Christie et al, 2007). However, also that approach is limited in the flexibility of varying the number of trips to respondents.

By merging CB and CE data where CB questions are related to the identical scenarios presented in the CE questions we are able to assess the value of the expected number of trips (use value) in the total economic value that respondents place on a recreational area. We find that failing to consider the expected number of trips in the random utility model that explains the choices to the CE questions may result in biased coefficient and willingness to pay estimates, and this is shown by the coefficient of the number of days being both positive and significant (model 6). We feel that this approach works particularly well for disentangling use and non use values in the demand for recreation. We see that people are willing to pay more for higher levels of infrastructure over the other three levels.

This paper has used simple poisson models and conditional logit models. Little investigation has been carried out for the heterogeneity among respondents. In future analysis we aim to explore more flexible models, such as mixed logit models to better capture the heterogeneity among respondents.

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