Attribute processing in environmental choice analysis: implications for willingness to pay

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Abstract

Data from a discrete choice experiment is used to investigate the implications of failing to account for attribute processing strategies (APSs). The research was designed to elicit the economic benefits associated with landscape restoration activities that were intended to remediate environmental damage caused by illegal dumping activities. In this paper we accommodate APSs using an equality constrained latent class model. By retrieving the conditional class membership probabilities we recover estimates of the weights that each respondent assigned to each attribute, which we subsequently use ensure unnecessary weight is not allocated to attributes not attended to by respondents. Results from the analysis provide strong evidence that significant gains in models fit as well as more defensible and reliable willingness to pay estimates can be achieved using when the APSs are accounted for.

Keywords: Attribute processing strategies; environmental restoration; equality constrained latent class model; multinomial logit model; willingness to pay

1 Introduction

Since its introduction by Louviere and Hensher (1982) and Louviere and Woodworth (1983) there has been a growing number of studies using the discrete choice experiment methodology. Discrete choice experiments are appealing as value derivation techniques because they are consistent with the Lancasterian microeconomic approach (Lancaster, 1966), whereby individuals derive utility from the different characteristics, or attributes, that a good possesses, rather than directly from the good *per se*. In discrete choice experiments, respondents are asked to select their preferred alternative from a given set (the choice set), and are typically asked to perform a sequence of such choices (Alpízar et al., 2003) giving rise to a panel of discrete choices. This type of analysis has been widely used to derive the economic benefits for ecological and environmental goods.

Typically, the estimation of discrete choice experiments assumes adherence to a number of axioms, most notably continuity. This axiom assumes unlimited substitutability amongst attributes and implies passive bounded rationality, whereby individuals consider all of the available information uniformly before making trade-offs between the attributes used to describe the alternatives (Puckett and Hensher, 2008). However, a growing literature has identified that is may be a somewhat unrealistic assumption—especially in situations where individuals are presented with complicated choice sets (e.g., see DeShazo and Fermo, 2004). As identified in Campbell et al. (2008); Hensher et al. (2005, 2010); Hess and Hensher (in press); Scarpa et al. (2009); Hensher et al. (2010) there is often process heterogeneity in the way that respondents evaluate bundles of attributes and in many situations it is found that respondents do not comply with the continuity assumption. In such cases respondents are said to adopt an attribute processing strategy (APS) whereby they behave in a rationally adaptive manner and focus solely on a subset of attributes, ignoring all other differences between attributes (Hensher, 2010).

Non-attending attributes in the choice set implies non-compensatory behaviour because no matter how much an attribute level is improved—if the attribute it-self is ignored by the respondent—then such improvement will fail to compensate for worsening in the levels of other attributes (e.g., Spash, 2000; Rekola, 2003; Sælensminde, 2002; Lockwood, 1996). Therefore, respondents using such APSs pose a problem for neoclassical analysis as they cannot be represented by a conventional utility function (Lancsar and Louviere, 2006). Without continuity, there is no trade-off between two different attributes (e.g., McIntosh and Ryan, 2002; Rosenberger et al., 2003; Gowdy and Mayumi, 2001). This is a key issue because without a trade-off, there is no computable marginal rate of substitution and, crucially for non-market valuation, no computable relative implicit price.

By better understanding how respondents attend to information within choice tasks, there is potential to greatly improve the design of choice models. Furthermore, from an econometric perspective there are obvious benefits in estimating choice models which condition the choices only on the basis of information that actually influences respondents' choices rather than assuming attendance to all information (DeShazo and Fermo, 2004). Welfare estimates are likely to be biased under modelling specifications that neither assume nor allow for violations of the continuity axiom and APSs. Indeed, growing evidence strongly advocates the use of models which have the capacity to accommodate violations of the continuity axiom and limit potential bias which could lead to subsequent inaccurate policy implications (Puckett and Hensher, 2008). For instance, DeShazo and Fermo (2004) and Campbell et al. (2008) demonstrate that models based on the standard passive bounded rationality assumption are distinctly different from those derived from a rationally-adaptive model which conditions parameter estimates on the APSs adopted by respondents. Under a rationally-adaptive model it is understood that individuals recognise that attending to all information would be complicated and in response employ an APS which will minimise the costs and maximise the benefits associated with information evaluation (DeShazo and Fermo, 2004). Swait (2001) further argues that accommodating such strategies can considerably improve the ability of the analyst to predict behavioural changes associated with proposed policy changes.

This paper focuses on this discussion and develops a modelling approach to account for APSs. We estimate three models. The first is a standard multinomial logit model which assumes compliance with the continuity axiom, thus implying that all respondents considered each and every attribute in their decision making. The second model is an equality constrained latent class model as proposed by Scarpa et al. (2009); Hensher et al. (2010), but where we assign a class for each and every possible APS. Using the derived conditional latent class membership probabilities, we estimate the weight that each respondent assigned to each of the attributes. We subsequently use these weights to condition the values of the parameters entering the log-likelihood function in a further multinomial logit model. This ensures that unnecessary weight is not allocated to attributes which respondents did not consider, and thus failed to influence their decision making. By reporting willingness to pay (WTP) estimates, this paper investigates the implications of failing to account for APSs. Results from the analysis provide evidence of a significant reduction in derived WTP estimates when APSs are accounted for in the estimation of discrete choice models. This paper uses data from a study designed to elicit the economic benefits associated with restoring environmental damage caused by illegal dumping. Our study focuses on an area close to Belfast in Northern Ireland, where illegal dumping activities are prevalent.

The paper is organised as follows. Section 2 outlines our methodological approach and model specifications. In Section 3 we present our study design. Section 4 presents the relevant results. Finally, Section 5 provides a discussion and offers a number of conclusions.

2 Methodological approach and model specifications

Starting with the conventional specification of utility, where respondents are indexed by n, chosen alternatives by i, and the vector of attributes are represented by x, we have:

$$U_{ni} = \beta' x_{ni} + \epsilon_{ni}, \tag{1}$$

where β are parameters to be estimated and ϵ is an *iid* Gumbel distributed error term, with constant variance $\pi^2/6$, giving rise to the multinomial logit model:

$$\operatorname{Prob}\left(U_{ni} > U_{nj}\right) = \frac{\exp\left(\beta' x_{ni}\right)}{\sum\limits_{i=1}^{J} \exp\left(\beta' x_{nj}\right)}.$$
(2)

While models of this form are widely used to quantify the economic costs and benefits associated with environmental goods and services, its estimation assumes adherence to the continuity axiom and thus implies passive bounded rationality. To expand the analysis, and reveal the implications of this often unrealistic, and even inappropriate, assumption, we use latent class models to endogenously assign respondents into latent segments that represent homogeneous APSs.

Latent class models are based on the assumption that individuals can be implicitly sorted into a set of exogenously defined *C* classes, each of which is characterised by unique class-specific utility parameters, β_c , for the attributes in the choice sets. Given membership to class *c*, the probability that individual *n* chooses alternative *i* over alternative *j* is based on a conventional random utility framework of the multinomial logit model:

$$\operatorname{Prob}\left(ni|c\right) = \frac{\exp\left(\beta_{c}'x_{ni}\right)}{\sum\limits_{j=1}^{J}\exp\left(\beta_{c}'x_{nj}\right)}.$$
(3)

In this paper, the objective of the latent class modelling is to derive the probabilities of respondents belonging to a class that represents a particular APS. This is achieved by extending the equality constrained latent class modelling approach proposed in Scarpa et al. (2009); Hensher et al. (2010). Under this approach, attribute non-attendance is accommodated by setting the utility coefficients in different latent classes to either zero or non-zero. This approach facilitates the identification of segments of the population who: considered all the attributes; adopted an APS by systematically ignoring one or more of the attributes thus only considering a subset of the available attributes; and, ignored all the attributes thus making a random choice between alternatives. An equality constraint on the parameters that are allowed to be non-zero is also used, so that when attributes are attended to, their utility weights take the same value across all classes, as commonly assumed in multinomial logit models.

Unlike Scarpa et al. (2009); Hensher et al. (2010) where the number of latent classes were restricted to explore APSs of interest, we allow for every possible permutation of APS. In this case the number of latent classes, C, is defined by 2^{K} , where K is the number of attributes used to describe the alternatives in the choice tasks. In our case we have 5 attributes, and the number of latent classes is thus 32. We present the structure of our equality constrained latent class model in Table 1. As may be seen, each class comprises of a combination of coefficients that are either set to zero or non-zero. Each class, therefore, represents a unique APS. In classes where the attribute coefficient is fixed to zero, the attribute is not attended to. Conversely, in classes where the attribute coefficient is not fixed to zero (i.e., estimated) the attribute is attended to. Also note that the values of these non-zero coefficients are constrained to be the same across all classes, so that preference, or taste, heterogeneity across respondents is not captured. This ensures that only the heterogeneity in attendance and non-attendance is captured, which is the central focus of this paper. Class 1 is associated with the segment of respondents who considered all five attributes, and thus comply with the continuity axiom. In this class all attributes are estimated by the model. This class is analogous with the basic MNL model and the conventional estimation of discrete choice experiments. Classes 2–6 represent the possible configurations where four out of the five attributes are considered. Respectively, classes 7-16and 17–26 correspond with the possible configurations where three and two of the attributes are considered by respondents. Classes 27–31 represent the possible configurations where only one of the attributes is considered. Finally, class 32 identifies the segment of respondents who ignored all five attributes.

With the individual probability of membership to a latent class c defined as π_c , it is possible to derive the unconditional probability of a sequence of choices, T_n , for individual n by taking the expectation over all the C classes:

$$\operatorname{Prob}\left(T_{n}\right) = \sum_{c=1}^{C} \pi_{c} \prod_{t=1}^{T_{n}} \frac{\exp\left(\beta_{nc}' x_{ni}\right)}{\sum_{j=1}^{J} \exp\left(\beta_{nc}' x_{nj}\right)},\tag{4}$$

where π and β , are parameters to be estimated in a regular maximum likelihood estimation procedure. Using these values and Bayes' formula, the conditional class probabilities, π_c^* can be obtained given the observed sequence of T_n choices:

nt	Dum	$\operatorname{p}(D)$	Water Qu	tality (<i>Wt</i>)	Wildlife H	abitats (<i>Wd</i>)	Outdoor R	ecreation (R)		Attributes
	A lot (A)	Some (S)	A lot (A)	Some (S)	A lot (A)	Some (S)	A lot (A)	Some (S)	Cost (\$)	considered
	β_{D_A}	β_{D_S}	β_{Wt_A}	β_{Wt_S}	β_{Wd_A}	β_{Wd_S}	β_{R_A}	β_{R_S}	β_{S}	5
 	0	<u>0</u>	$\dot{\beta} = -\frac{1}{\beta} \frac{1}{M_{I_A}} = -\frac{1}{\beta}$	$\overline{\beta}W_{tS}$ $$	$ \frac{\beta}{\beta} = $	$ \frac{\beta}{\beta} \frac{\delta}{Wd_S}$	$ \beta_{R_A}$	$\frac{1}{\beta R_S}$	$ \frac{\beta_s}{\beta_s}$	
	β_{D_A}	β_{D_S}	0	0	β_{Wd_A}	β_{Wd_S}	β_{R_A}	β_{R_S}	$\beta_{\$}$	
	β_{D_A}	β_{D_S}	β_{Wt_A}	β_{Wt_S}	0	0	β_{R_A}	β_{R_S}	$\beta_{\$}$	4
	β_{D_A}	β_{D_S}	β_{Wt_A}	β_{Wt_S}	β_{Wd_A}	β_{Wd_S}	0	0	$\beta_{\$}$	
	β_{D_A}	β_{DS}	β_{Wt_A}	β_{Wt_S}	β_{Wd_A}	β_{WdS}	β_{R_A}	β_{R_S}	0	
, 		$\frac{1}{2}$ $\frac{1}$			$= -\frac{\beta}{\beta} \frac{\beta}{Wd_A} = -\frac{\beta}{2}$	$ \frac{\beta}{\beta} \frac{\beta}{Wd_S}$	$=$ $=$ $=$ $\frac{\beta_{R_A}}{\beta_{R_A}}$ $=$ $=$	$=$ $-\frac{\beta}{\beta}_{R_S}$ $=$ $ -$	$ \frac{\beta_s}{\beta_s}$	
	0	0	β_{Wt_A}	β_{Wt_S}	0	0	β_{R_A}	β_{R_S}	$\beta_{\$}$	
	0	0	β_{Wt_A}	β_{Wt_S}	β_{Wd_A}	β_{Wd_S}	0	0	$\beta_{\$}$	
	0	0	β_{Wt_A}	β_{Wt_S}	β_{Wd_A}	β_{Wd_S}	β_{R_A}	β_{R_S}	0	
	β_{D_A}	β_{D_S}	0	0	0	0	β_{R_A}	β_{R_S}	$\beta_{\$}$	"
	β_{D_A}	β_{D_S}	0	0	β_{Wd_A}	β_{Wd_S}	0	0	$\beta_{\$}$	C.
	β_{D_A}	β_{D_S}	0	0	β_{Wd_A}	β_{Wd_S}	β_{R_A}	β_{R_S}	0	
	β_{D_A}	β_{D_S}	β_{Wt_A}	β_{Wt_S}	0	0	0	0	$\beta_{\$}$	
	β_{D_A}	β_{D_S}	β_{Wt_A}	β_{Wt_S}	0	0	β_{R_A}	β_{R_S}	0	
	β_{D_A}	β_{D_S}	β_{Wt_A}	β_{Wt_S}	β_{Wd_A}	β_{Wd_S}	0	0	0	
 		0	0 			<u>0</u>	$ \beta_{R_A}$	$ \frac{\beta}{\beta}R_{S}$	$\beta_{s} = -\beta_{s} = -\beta_{s}$	
	0	0	0	0	β_{Wd_A}	β_{Wd_S}	0	0	$\beta_{\$}$	
	0	0	0	0	β_{Wd_A}	β_{Wd_S}	β_{R_A}	β_{R_S}	0	
	0	0	β_{Wt_A}	β_{Wt_S}	0	0	0	0	$\beta_{\$}$	
	0	0	β_{Wt_A}	β_{Wt_S}	0	0	β_{R_A}	β_{R_S}	0	2
	0	0	β_{Wt_A}	β_{Wt_S}	β_{Wd_A}	β_{Wd_S}	0	0	0	
	β_{D_A}	β_{D_S}	0	0	0	0	0	0	$\beta_{\$}$	
	β_{D_A}	β_{D_S}	0	0	0	0	β_{R_A}	β_{R_S}	0	
	β_{D_A}	β_{D_S}	0	0	β_{Wd_A}	β_{Wd_S}	0	0	0	
	β_{D_A}	β_{D_S}	β_{Wt_A}	β_{Wt_S}	0	0	0	0	0	
	0	0	0	0	0	0	0	0	βş	
	0	0	0	0	0	0	β_{R_A}	β_{R_S}	0	
	0	0	0	0	β_{Wd_A}	β_{Wd_S}	0	0	0	
	0	0	β_{Wt_A}	β_{Wt_S}	0	0	0	0	0	T
	β_{D_A}	β_{D_S}	0	0	0	0	0	0	0	
, 	$\frac{1}{2} - \frac{1}{2} - \frac{1}$	$\frac{1}{2}$ $\frac{1}$				0		$\frac{1}{2}$ $\frac{1}$	0	

Table 1: Equality constrained latent class structure

D. Campbell, V. Lorimer, C. Aravena and G. Hutchinson

$$\pi_{c}^{*} = \operatorname{Prob}\left(n \in c | y_{T_{n}}, x_{T_{n}}\right) = \frac{\pi_{c} \prod_{t=1}^{T_{n}} \frac{\exp(\beta_{nc}' x_{ni})}{\sum\limits_{j=1}^{L} \exp(\beta_{nc}' x_{nj})}}{\sum\limits_{c=1}^{C} \pi_{c} \prod\limits_{t=1}^{T_{n}} \frac{\exp(\beta_{nc}' x_{ni})}{\sum\limits_{j=1}^{L} \exp(\beta_{nc}' x_{nj})}},$$
(5)

where y_{T_n} and x_{T_n} are, respectively, the observed choices and the attributes of the chosen alternatives.

With this set of indivdual-specific probabilities we can predict the proportion of respondents who adopted each of the APSs. However, of greater interest in this paper are the probabilities that respondents attended to the attributes. This can be achieved by summing the individual-specific probabilities for latent classes where the attribute of interest is non-zero (i.e., classes in which the attribute is assumed to be attended to). For instance, using the latent class structure reported in Table 1 an estimate of the attention that a respondent allocated to the Cost attribute can be obtained by adding together the individual-specific membership probabilities of classes 6, 10, 13, 15–16, 19, 21–22, 24–26 and 28–32. If this is estimated to be close to zero it implies that the respondent paid little attention to the attribute.

The individual-specific probabilities retrieved under our latent class model are, therefore, very informative as they enable inferences to be made regarding the weight that each respondent assigned to each attribute. Importantly, these weights provide helpful information that can be incorporated within the econometric model. For this reason, we propose using the individual-specific weights to condition the parameters entering the discrete choice model. We achieve this by multiplying each of the K attributes by the individual-specific probabilities of attribute attendance and estimating a further MNL model as follows:

$$\operatorname{Prob}(ni) = \frac{\exp\left(\left(\omega_{nk}\beta_{k}\right)' x_{ni}\right)}{\sum_{j=1}^{J} \exp\left(\left(\omega_{nk}\beta_{k}\right)' x_{nj}\right)},\tag{6}$$

where ω_{nk} denotes the probability (i.e., weight) that respondent *n* attended to attribute *k*. This ensures that the choice probabilities are constructed in such a way that the actual elements of β that enter the likelihood function are weighted by the attention that each respondent allocated to each attribute. This approach should produce more accurate utility expressions and, hence, lead to improvements in model performance and welfare estimation.

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3 Study design

The introduction of the EU Environmental Liability Directive (2004/35/CE) establishes a common framework for the prevention and remediation of environmental damage. This is achieved by providing a statutory basis for a range of restoration activities that are intended to re-establish the environment to its original condition. This research sought to provide an insight into public preferences for the kind of environmental restoration activities endorsed by the Directive thereby providing policy makers with information to efficiently target their restoration efforts.

Under the Directive a wide-range of restoration activities are possible. We use a multi-attribute valuation approach (discrete choice experiment) to study trade-offs and values associated with different policy designs. The Belfast Hills in Northern Ireland, where environmental damage arising from ongoing illegal dumping is prevalent, is used as a case-study. Specifically, we use this case-study to assess the public's *WTP* for the kind of restoration activities promoted by the EU Environmental Liability Directive to address environmental damage caused by illegal dumping. Restoration activities are intended to restore the area by conserving the environment, promoting sustainability and reducing the loss of biodiversity.

The discrete choice experiment reported in this paper involved several rounds of design and testing. This process began with the gathering of opinions from stakeholders. Having identified the initial attributes, a series of focus group discussions with members of the public were held. Following the focus group discussions, the questionnaire was piloted in order to check whether the wording and format used was appropriate and if respondents were able to understand the discrete choice experiment exercises.

In the final design of the questionnaire four attributes were used to describe the restoration activities. Restorative attributes were categorised as improvements that could take place at the illegal dump sites or general improvements that could take place elsewhere within the Belfast Hills boundary. This distinction was made to coincide with the EU Environmental Liability Directive which stipulates remediation to take place either at the damaged site (i.e., on site) or at an alternative location geographically linked to the damaged site (i.e., off-site). The discrete choice experiment contained one on-site restoration attribute: improvement at the Dump Sites (D), and three complementary, or off-site, restoration attributes: improvement to Water Quality (Wt), Wildlife Habitats (Wd) and Outdoor Recreation (R). For each restoration attribute, three possible levels of improvement were available. To lessen the cognitive burden on the respondent, these levels were consistent for each attribute. They were described as A Lot of Improvement (A), Some Improvement (S) and No Improvement (N). Each of which was explained in terms of the level of improvement that would be achieved through their implementation. The Cost attribute (\$) was described as a one-off cost (in Sterling Pounds) that the respondent would personally have to pay to implement the alternative. The discrete choice experiment consisted of a panel of six repeated choice tasks. For each choice task, respondents were asked to indicate their preferred alternative among two experimentally designed generic alternatives—labelled Option A and Option B. Each choice task also included a Do Nothing option—which portrayed all the restoration attributes at the No Improvement level with zero cost to the respondent. An example of a choice task is presented in Figure 1.

When making their choices, respondents were asked to consider only the attributes presented in the choice task and to treat each choice task independently. In an attempt to minimize hypothetical bias, respondents were also reminded to take into account whether they thought restoring the environmental damage was



If instead, there was a 'DO NOTHING' option available—which would mean nothing would be done to deal with the unauthorised dumping and would cost you nothing extra—would the 'DO NOTHING' option be your most preferred?



Figure 1: Example of a choice task presented to respondents

worth the payment asked of them and were made aware that environmental protection is embedded in an array of substitute and complementary goods. In total, 3234 observables were obtained from a random sample of 556 respondents.

4 Results

4.1 Estimation results

Table 2 reports the estimation results for three models. Model 1 pertains to the estimation of the data using a standard multinomial logit specification (Equation 2), which assumes full attribute attention (i.e., passive bounded rationality). Whereas, Models 2 and 3 are alternative specifications which attempt to account for the heterogeneity in respondent's APSs (i.e., rationally adaptive behaviour). Model 2 is an equality constrained latent class model (Equation 4) using the class structures given in Table 1. While the first two models make use of the data in its original form, Model 3 is is a further multinomial logit model (Equation 6) that makes use of the individual-specific probabilities of attribute attendance retrieved from Model 2.

Under Model 1, all parameters are estimated as significant and are in line with expectations (with the exception that β_{R_s} is estimated with a higher coefficient than β_{R_A}). In Model 2, the attribute parameters are again significant and are all estimated with expected signs and magnitudes expectations (including β_{R_A} and β_{R_s}). Of central interest in Model 2 are the retrieved class membership probabilities, which are reported in Figure 2. Examination of the latent class probabilities,

	Мос	lel 1	Mod	lel 2ª	Mod	lel 3
	est.	t-ratio	est.	t-ratio	est.	t-ratio
β_{D_A}	1.693	19.8	4.418	16.2	6.741	23.4
β_{D_S}	1.408	23.9	3.471	17.4	4.672	22.4
β_{Wt_A}	1.303	19.0	4.199	12.8	5.961	22.0
β_{Wt_S}	0.962	16.0	2.972	11.3	4.045	18.4
β_{Wd_A}	1.332	18.5	4.190	14.9	5.976	21.5
β_{Wd_S}	0.929	15.5	2.780	12.8	3.780	18.0
β_{R_A}	0.374	5.3	2.528	6.1	4.912	15.4
β_{R_S}	0.490	7.9	2.168	6.9	3.796	13.4
$eta_{\$}$	-0.019	-6.3	-0.196	-11.4	-0.384	-19.4
$\mathcal{L}(\hat{eta})$	-2,00	8.143	-1,70	0.230	-555	.340
$ ho^2$	0.4	35	0.5	521	0.8	344
AIC	4,034	4.286	3,480	0.461	1,128	8.680
BIC	4,089	9.019	3,653	3.292	1,183	3.413

Table 2. Estimation results	Tabl	e 2:	Estimation	ı results
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^a Latent class probabilities are depicted in Figure 2.



suggest that only a very small proportion of respondents (0.6%) considered all attributes. According to our results, we find instead considerable heterogeneity in the APSs adopted by respondents. Notably, we remark that the aggregate membership probability for ignoring one attribute (i.e., classes 2–6) is 28.8%. Respectively, we further find that the total membership probabilities for ignoring two attributes (i.e., classes 7–16) and three attributes (i.e., classes 17–26) are 22.8% and 25.4%. Importantly, the sum of classes in which respondents attended to only one attribute (i.e., classes 27–31) is found to be 22.4%. Less than 0.1% of respondents are identified as belonging to the class in which all attributes are not attended to (i.e., class 32).

Turning our attention to the probabilities of the latent classes where each of the environmental restoration attributes have a non-zero coefficient, our results indicate that: Dump Sites is the most attended to (76.0%); Outdoor Recreation is the least attended to (40.9%); with Wildlife Habitats (61.5%) and Water Quality (57.7%) ranking in-between. Crucially, we find the respective figure for the Cost attribute to be 23.6%, which implies that less than one-quarter of the respondents considered the level of cost associated with each of the alternatives in the choice experiment. To further illustrate, we present in Figure 3 histograms of the conditional probabilities of attendance to each of the attributes. While the conditional distributions of attendance to Water Quality (Figure 3(b)), Wildlife Habitats (Figure 3(c)) and Outdoor Recreation (Figure 3(d)) are relatively uniform, the distributions for Dump Sites (Figure 3(a)) and Cost (Figure 3(e)) are skewed to left and right respectively.

The parameters in Model 3 in Table 2, which conditions the parameters according to the estimated probability that each respondent attended to the attribute, are also found to be significant with the expected signs and magnitude. While all three models are found to have acceptable ρ^2 values, as reflected by the increase in log-likelihood, there is an huge improvement in model fit as one moves from Model 1 to Model 3.

4.2 Welfare estimates

An alternative way of teasing out the effect of failing to accommodate APSs is to consider the effects on the estimated values of *WTP*. Table 3 reports the marginal *WTP* estimates for each attribute obtained from our three models, which are computed using the ratios, β_k/β_s . Confidence intervals are also reported to enable inferences on statistical precision to be made. Additionally, we also report the average of the marginal *WTP* estimates under each model to facilitate straightforward comparison between the models.

Importantly, all WTP estimates are statistically significant. But of greater interest are the differences in magnitudes across the three models. An examination of the marginal WTP estimates obtained from the multinomial logit model



Figure 3: Histograms of attribute attendance

based on the standard assumption of passive bounded rationality are high, and exceed what we consider represents realistic *WTP* estimates. However, in line with findings reported elsewhere (e.g., Campbell et al., 2008; Hensher et al., 2010; Scarpa et al., 2009), we remark a sharp decline in the estimated *WTP* values in both rationally-adaptive models. Indeed, compared to Model 1, average

	Model 1	Model 2	Model 3
WTD	90.07	22.54	17.54
WIP_{D_A}	(64.24–115.91)	(17.99–27.09)	(15.86–19.22)
WTD	74.90	17.71	12.16
WIP_{D_S}	(53.06–96.74)	(14.41-21.01)	(10.94–13.38)
WTP	69.34	21.42	15.51
WIP_{WtA}	(48.38–90.29)	(16.63–26.22)	(14.21–16.81)
WTP_{Wts}	51.16	15.16	10.52
WIP_{Wts}	(35.17-67.15)	(11.64–18.68)	(9.34–11.71)
WTD	70.85	21.38	15.55
WIP_{Wd_A}	(50.45-91.24)	(17.05–25.71)	(14.13–16.97)
WTD	49.41	14.18	9.84
WIP_{Wds}	(33.90-64.92)	(11.12–17.25)	(8.59–11.08)
WTD	19.90	12.90	12.78
WIP_{R_A}	(11.01-28.78)	(7.79–18.00)	(11.52 - 14.04)
WTD	26.08	11.06	9.88
WIP_{R_S}	(16.89–35.27)	(7.60–14.52)	(8.51–11.24)
Average	56.46	17.04	12.97
Average	(40.61–72.31)	(14.09–20.00)	(12.07–13.88)

Table 3: Marginal WTP estimates in $\pounds s^a$

^a 95% confidence interval in parenthesis.

WTP estimates for Models 2 and 3 are almost 70% and 80% lower respectively. Moreover, the confidence intervals for the *WTP* estimates under Model 1 do not overlap with those obtained in either Models 2 or 3. We note a further reduction in the *WTP* estimates under Model 3 compared to Model 2, albeit with overlapping confidence intervals for some of the attributes. We do remark, however, that scrutiny of these confidence intervals reveals that they are relatively much tighter under Model 3—implying that conditioning the attribute parameters on the basis of weights attribute attendance leads to welfare estimates that are statistically more robust and reliable.

Aside from the magnitudes and statistical precision of the *WTP* estimates, we find that the implied rank orderings are quite stable across the four model specifications. Nonetheless, we find that the relative difference between the various restoration attributes diminishes. Most notably, the disparity between the on-site (i.e., Dump Sites) and off-site restoration attributes (i.e., Water Quality, Wildlife Habitats and Outdoor Recreation) under Model 1, is not evident under Models 2 and 3.

5 Discussion and conclusion

Choice experiments, as an environmental valuation technique, were employed in this research to determine public preference for a range of restoration activities in compliance with the European Liability Directive (2004/35/CE) to restore en-

vironmental damage arising from illegal dumping activities in the Belfast Hills. Examination of the results reveals public support for each proposed restoration activity with a distinct preference for 'on-site' restoration activities (which attempt to directly restore the damaged sites towards their original condition) over 'off-site' restoration activities (which are aimed at compensating for the environmental degradation by remediating or improving a geographically linked site). From the two proposed 'on-site' activities the public value the permanence associated with 'A Lot' of improvement more highly than more provisional activities attached to 'Some' improvement of the sites. Nevertheless, 'off-site' restoration activities were also highly favoured, especially environmental improvements associated with water quality and wildlife habitats.

Conventionally the estimation of discrete choice experiments assumes compliance to the continuity axiom whereby it is assumed that respondents consider all attributes before engaging in a trade-off to select their preferred alternative. But as shown in this paper, and in numerous other studies, this assumption may not always be appropriate. In this paper we facilitate APSs using an equality constrained latent class approach. Specificity, we specify the structure of the latent classes to obtain probabilistic estimates of all possible APSs. We show that significant gains in model fit can be achieved using this approach. We additionally demonstrate how the results can be used to retrieve the probabilities of each respondent attending to the attributes, which can further be used to inform the modelling specification to enhance model fit. We find evidence that the WTP estimates attached to the restoration activities are extremely sensitive to APSs. Estimates attained from the model based on the assumption of passive bounded rationality are found to be much higher than those based on the rationally-adaptive assumptions. Derived WTP estimates from our informed model were generally markedly lower and were all statistically more robust. Importantly these estimates had tighter confidence intervals and were more economically defensible meaning that they are more appropriate for use to formulate policy recommendations.

Results presented here draw attention to the potential consequences and repercussions for policy appraisal and evaluation of estimating discrete choice experiments based on the assumption of passive bounded rationality. Our results suggest some caution when APSs are neglected when discrete choice models are used for policy analysis. The findings also provide compelling evidence for further research in this area. Future studies should incorporate procedures for identifying and dealing with attribute processing strategies so that the sensitivity on model performance and welfare estimates can be further evaluated.

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