Bounding WTP distributions to reflect the ‘actual’ consideration set

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In this paper we extend the independent availability logit and combined latent class mixed logit models to accommodate respondents with different consideration sets due to their cost thresholds and cut-offs. Pertinent features of our model are that it is estimated in WTP-space and that the class-specific WTP distributions are truncated to be within the bounds deduced from the cost level(s) within each class-specific consideration set. Our analysis shows that our approach is well suited at uncovering the heterogeneity in the cost thresholds and cut-offs used by respondents. This is shown to help build a richer insight into respondent’s behaviour as well as raise a number of concerns about the appropriateness of assuming deterministic choice sets. We discuss the implications of our results for welfare analysis.

Keywords: independent availability logit model • combined latent class mixed logit model • willingness to pay • consideration set • cost threshold.

1 Introduction

When analysing discrete choice data, especially stated choice data, it is typically assumed that respondents consider all offered alternatives and their choices are based on the alternatives that provide them with the highest utility. However, at least in principle, one may postulate the hypothesis that due to differences in personal budget constraints, as well as preferences, respondents may restrict their consideration set to those alternatives that do not exceed their cost (as well as other) thresholds and cut-offs (cf., Swait, 2001; Han et al., 2001; Cantillo et al., 2006; Cantillo and Ortúzar, 2006; Chou et al., 2008; Mørkbak et al., 2010; Campbell et al., 2011, 2012). If this is indeed the case, failing to account for this processing strategy is likely to be suboptimal, and perhaps lead to misguided inferences, as the model does not reflect actual choice behaviour.

The alternatives taken into account by a respondent cannot be known with certainty. Indeed, recent studies ask whether an alternative is acceptable or not (e.g., see Hensher and Rose, 2012; Doherty et al., 2013). However, observed choice behaviour helps make probabilistic statements about the likelihood of competing consideration sets being the true choice set. Following Manski (1977), a probabilistic framework can be formulated to model this type of behaviour to help distinguish between the deterministic choice set, as generated by the experimental design, and the respondent’s ‘actual’ consideration set. For this type of analysis we extend the independent availability logit (IAL) model (cf. Swait and Ben-Akiva, 1987; Swait, 2001) to accommodate respondents with different consideration sets due to their cost thresholds and cut-offs. Since a respondent’s true consideration set cannot be known with certainty, this model assumes that the choice sets are latent, and, in our case, the conditional choice model is mixed logit.

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Our work is motivated by the fact that greater behavioural insights into the alternatives that actually have an influence on respondent’s choices should help at the analytical stage, particularly when it comes to deriving reliable welfare estimates. Indeed, an especially important feature of the insight into the cost level(s) of the restricted choice sets is that it gives an indication of the bounds of the aggregate marginal willingness to pay (WTP) distribution. If some respondents systematically restrict their actual choice set to only include alternatives that are below a given cost level, their maximum aggregate marginal WTP can be safely assumed to be less than this cost threshold. Similarly, a lower bound for their minimum aggregate marginal WTP can be identified, which is, clearly, at least the value of the highest cost level within their true consideration set. To accommodate this insight we further broaden the IAL model. Similar to what is done in latent class models with continuous distributions of random parameters within classes, we accommodate within-class heterogeneity. Albeit the classes in this case denote competing consideration sets as opposed to different taste structures.

1 Salient features of our proposed model are that (i) it is estimated in WTP-space and (ii) that the class-specific WTP distributions are truncated to be within the bounds deduced from the cost level(s) within each class-specific consideration set.

Our analysis shows that our approach is well suited at uncovering the heterogeneity in the cost thresholds and cut-offs used by respondents. This is shown to help build a richer insight into respondent’s behaviour as well as raise a number of concerns about the appropriateness of assuming deterministic choice sets. The empirical application of our modelling approach shows that it has important implications for welfare analysis.

The rest of the paper is organised as follows. Section 2 describes our econometric approach and Section 3 presents our empirical context. Section 4 reports the model estimation and post estimation results. Section 5 concludes.

2 Method

We derive marginal WTP estimates using the framework of discrete choice models based on random utility maximisation (RUM). We start by introducing the required notation so as to provide a base model against which comparisons can be made. Then, we illustrate our model to facilitate the fact that some respondents may have rationally and systematically excluded some of the proposed alternatives from their consideration set at the moment of choice. Further, we then extend this model by ensuring that the fact that some respondents may have excluded some alternatives from their consideration set. We then extend this model by ensuring that the marginal WTP estimates reflect the bounds implied by the restricted choice sets. We go on to explain how we concurrently address the heterogeneity in respondent’s marginal WTP. We round-up this section by detailing our approach to model estimation.

2.1 Background notation

We use the conventional approach to analyse discrete choice experiment data, based on RUM, where individuals are assumed to select the choice alternative that yields the greatest expected utility to them. In particular, where respondents are indexed by \( n \), choice occasions by \( t \), the price and non-price attributes are represented by \( p \) and \( x \) respectively, the utility of the chosen alternative \( i \), can be written as:

\[
U_{nit} = -\alpha p_{nit} + \beta x_{nit} + \epsilon_{nit}, \tag{1a}
\]

where \( \alpha \) and \( \beta \) are parameters to be estimated for the price and non-price attributes respectively, and \( \epsilon \) is an iid type I extreme value (EV1) distributed error term, with constant variance of \( \pi^2/6 \). The specification in Eq. (1a) parameterises utility in ‘preference-space’. Given the focus of this paper is to uncover respondent’s marginal WTP, we prefer to work in ‘WTP-space’, as promoted by Train and Weeks (2005) and Scarpa et al. (2008). The implied marginal WTP for an attribute is the ratio of the attribute’s coefficient to the price coefficient: \( w = \beta/\alpha \). Using this definition, utility can be rewritten as:

\[
U_{nit} = -\alpha p_{nit} + (\alpha w) x_{nit} + \epsilon_{nit}, \tag{1b}
\]

which is called utility in WTP-space because \( w \) represent a vector of marginal WTPs for the respective attributes. Expressing utility in this manner has the advantage that the estimates of marginal WTP are

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1 We note, in passing, that this framework can easily be generalised to account for thresholds in more than one attribute. In fact, the approach lends itself to exploring a range of ‘elimination-by-aspects’ behaviour (i.e., where the choice procedure is a process of eliminating alternatives that do not fulfill certain aspects).
reported directly in the model output by the vector of estimates \( \hat{w} \). Moreover, the coefficient estimates obtained for \( \hat{w} \) are independent from those obtained for the price coefficient \( \hat{d} \), meaning that the instability associated with marginal WTP estimates derived from the ratio of random variables in preference-space is reduced (Balcombe et al., 2010; Hensher and Greene, 2011).

Given the assumptions outlined above, the probability of the sequence of choices made by individual \( n \) can be represented by the MNL model:

\[
Pr\{y_n|p_n, x_n\} = \prod_{t=1}^{T_n} \frac{\exp(-a p_{nit} + (a u) x_{nit})}{\sum_{j=1}^{J} \exp(-a p_{njt} + (a u) x_{njt})},
\]

where \( y_n \) gives the sequence of choices over the \( T_n \) choice occasions for respondent \( n \), i.e., \( y_n = \langle i_{n1}, i_{n2}, \ldots, i_{nT_n} \rangle \).

### 2.2 Accounting for endogenous WTP bounds

While the MNL model expressed in Eq. (2) directly uncovers estimates of marginal WTP for various attributes, in the typical stated choice experiment it does so in a manner that assumes all respondents consider all offered alternatives, including those that are priced higher than their maximum marginal WTP. However, since respondents may rationally restrict their consideration set to include only those alternatives that do not exceed their maximum marginal WTP, this assumption may not necessarily be appropriate. Following Manski (1977), a probabilistic model can be formulated to model this type of behaviour to help distinguish between the deterministic choice set, as generated by the experimental design, and the respondent’s actual consideration set from the alternatives offered in the choice experiment. For this type of analysis we extend the independent availability logit (IAL) (cf. Swait and Ben-Akiva, 1987; Frejinger et al., 2009; Kaplan et al., 2012; Richardson, 1982; Ben-Akiva and Boccara, 1995; Louviere et al., 2000, for some examples). The probability of choice in the IAL model is given by:

\[
Pr\{y_n|C_s, p_n, x_n\} = \sum_{i=1}^{S} \pi_i \prod_{j=1}^{T_n} Pr\{y_{nj}|C_i, p_n, x_n\},
\]

(3a)

where \( Pr\{y_{nj}|C_i, p_n, x_n\} \) is the conditional probability of the sequence of choices given the choice set is \( C_i \subseteq S \), \( S \) is the set of subsets, \( \pi_i \) is the probability that \( C_i \) is the ‘true’ choice set. Since a respondent’s true consideration set cannot be known with certainty, the model assumes that choice sets are latent and vary across the \( S \) classes, while the conditional choice model is MNL:

\[
Pr\{y_{nj}|C_i, p_n, x_n\} = \prod_{t=1}^{T_n} \frac{\exp(-a p_{nit} + (a u) x_{nit})}{\sum_{j \in C_i} \exp(-a p_{njt} + (a u) x_{njt})}.
\]

(3b)

Typically in an IAL model, the number of classes, \( S \), is determined as a function of the number of alternatives (e.g., for a universal set with \( J \) alternatives, there are \( 2^J \) possible choice sets). In this paper, however, we are interested in exploring whether respondents restrict their choice set on the basis of the cost attribute. For example, in the situation where there are four cost levels, \( p = \{\£0, \£1, \£2, \£3\} \), four types of behaviour can be identified:

- **Class 1**: a subset whose actual choice set is the same as the set offered in the choice experiment;
- **Class 2**: a subset who restrict their actual choice set to include alternatives that cost less than \( \£3 \);
- **Class 3**: a subset who restrict their actual choice set to include alternatives that cost less than \( \£2 \); and,
- **Class 4**: a subset who restrict their actual choice set to include alternatives that cost less than \( \£1 \).

These four patterns can be dealt with using an IAL model with four classes, where each class describes a unique consideration set.

As noted above, the alternatives taken into account by a respondent cannot be known with certainty. However, their observed choice behaviour helps make probabilistic statements about the likelihood of competing consideration sets being their true choice set. These (unconditional) probabilities can be

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2For further discussion on WTP-space models see Train and Weeks (2005) and Scarpa et al. (2008).

3We recognise that further classes could be defined if we also consider lower thresholds (e.g., see Campbell et al., 2012).
derived using a further MNL model:

$$\pi_s = \frac{\exp(\theta_s)}{\sum_{s=1}^{S} \exp(\theta_s)}, \quad (3c)$$

where $\theta_s$ denotes the constant corresponding to the class with consideration set $C_s$, and where, for identification purposes, $\theta_S$ is set to zero.

An especially important feature of the insight into the cost level(s) of the restricted choice sets is that it gives an indication of the bounds of the aggregate marginal WTP values. That is, if some respondents systematically restrict their actual choice set to only include alternatives that are below a given cost threshold, their maximum aggregate marginal WTP can be safely assumed to be less than this upper cost threshold, $p_{u_k}$. Similarly, a lower bound, $p_{l_k}$, for their minimum aggregate marginal WTP can be identified, which is, clearly, at least the value of the highest cost level, within their true consideration set.

To accommodate this insight we further broaden the IAL model. That is, we specify the IAL model with class-specific marginal WTP values as follows:

$$\Pr\{y_n|p_n, x_n\} = \sum_{s=1}^{S} \pi_s \prod_{t=1}^{T_s} \frac{\exp(-\alpha p_{nit} + (\alpha w_{nit}) x_{nit})}{\sum_{j \in C_s} \exp(-\alpha p_{nit} + (\alpha w_{nit}) x_{nit})}, \quad (4)$$

where $p_{l_k} \leq \sum_{k=1}^{K} w_{nit} < p_{u_k}$. Restrictions are imposed to ensure that the aggregated marginal WTP estimates for the $K$ non-cost attributes are within the bounds implied by the consideration set. We remark that for the latent class associated with the deterministic choice it is only necessary to impose the restriction $\sum_{k=1}^{K} w_{nit} \geq p_{l_k}$. We also highlight that it is not possible to compute marginal WTP estimates for the class that restricted their choice sets to only zero priced alternatives. We are mindful of the potential confounding between the type of behaviour we are trying to capture and the recovery of preference heterogeneity, a point to which we return later.

### 2.3 Accounting for the heterogeneity in marginal WTP

While the assumption of homogeneity in the values that respondents are willing to pay may hold in some cases, for a variety of reasons the values are likely to be heterogeneous across respondents. Consequently, we are also interested in capturing the heterogeneity in respondents’ marginal WTP within consideration set classes. For this reason, we treat $\alpha_n$ and $\tilde{w}_n$ as continuously distributed random terms entering the of the WTP-space utility function.

If the values of $\alpha_n$ and $\tilde{w}_n$, as well as $C_{sn}$, were known with certainty for each respondent $n$, then the probability of respondent $n$’s sequence of choices would be given by:

$$\Pr\{y_n|C_{sn}, \alpha_n, w_n, p_n, x_n\} = \prod_{t=1}^{T_s} \frac{\exp(-\alpha_n p_{nit} + (\alpha_n w_{nit}) x_{nit})}{\sum_{j \in C_{sn}} \exp(-\alpha_n p_{nit} + (\alpha_n w_{nit}) x_{nit})}, \quad (5)$$

However, it is clearly not possible to know either $\alpha_n$, $w_n$ or $C_{sn}$ with certainty for each respondent $n$. For this reason, in estimation, we accommodate heterogeneity across respondents by allowing for random variation. Denote the joint density of $[\alpha_n, w_{n1}, w_{n2}, \ldots, w_{nK}]$ by $f(\Theta_n|\Omega)$, where $\Theta_n$ represents the vector comprised of the random parameters and $\Omega$ denotes the class-specific parameters of these distributions (e.g., the mean and variance). The unconditional choice probability is the integral of the logit formula over all possible values of $\alpha_n$ and $\tilde{w}_n$ weighted by the class probabilities to also integrate out the different $C_{sn}$:

$$\Pr\{y_n|w_n, p_n, x_n, \Omega\} = \sum_{s=1}^{S} \pi_s \prod_{t=1}^{T_s} \frac{\exp(-\tilde{\alpha}_n p_{nit} + (\tilde{\alpha}_n \tilde{w}_n) x_{nit})}{\sum_{j \in C_{sn}} \exp(-\tilde{\alpha}_n p_{nit} + (\tilde{\alpha}_n \tilde{w}_n) x_{nit})} f(\Theta_n|\Omega) \, d(\Theta_n). \quad (6)$$

In this combined latent class random parameters logit (LC-RPL) (e.g., Bujosa et al. (2010); Greene and Hensher (2013); Campbell et al. (2013, for general applications) and Hess et al. (2012); Hensher et al. (2012, for applications focusing on processing strategies)) specification, parameters of the distributions (i.e., $\Omega$) and probabilities associated with each consideration set based on cost thresholds are obtained. Again, restrictions can be placed on the marginal WTP distributions to ensure that they are within the
bounds characterised by the consideration set.

**2.4 Model estimation**

The MNL model (Eq. (2)) and our IAL model to facilitate marginal WTP bounds (Eq. (4)) are estimated using maximum likelihood estimation, whereas, since the choice probabilities in the LC-RPL model (Eq. (6)) cannot be calculated exactly (because the integrals do not have a closed form), they are approximated by simulating the log-likelihood with 350 quasi-random draws via Modified Latin Hypercube Sampling (cf. Hess et al., 2006). In the case of the models that also retrieve class probabilities, we are also mindful of the fact that models of this form are subject to local maxima. Thus, in an attempt to reduce the likelihood of reaching a local rather than a global maximum, we use a variety of random starting points. Specifically, we do this by estimating these models many times, but each time using a different vector of starting values, which are chosen randomly.

A key element with the specification of random taste variation is the assumption regarding the distribution of each of the random parameters (Hensher and Greene, 2003; Hess et al., 2005). Random parameters can take a number of predefined functional forms. Given the theoretical expectations of disutility for increasing cost, the fact that it is not possible to separately identify the price and scale parameters, as well as the established practice in WTP-space models (e.g., Balcombe et al., 2010; Scarpa et al., 2008; Thiene and Scarpa, 2009), we specify with a log-Normal distribution to ensure strictly negative values for the price/scale coefficient as follows: \( \alpha = \exp(\mu + \sigma \nu) \), where \( \nu \) is a standard Normal deviate and \( \mu \) and \( \sigma \) are the parameters to be estimated. We note that to facilitate identification, we do not estimate class specific values for \( \mu \) and \( \sigma \).

A key aspect of our approach is that the class-specific marginal WTP distributions, \( w_k \), respect the bounds implied by the consideration set. This means that finite lower, \( a_k \), and upper limits, \( b_k \), are necessary (i.e., \( \sum a_k \geq p_i \) and \( \sum b_k < p_{nu} \)). After evaluating the results from various specifications and distributional assumptions, for the distributions of \( w_k \) we opt for Uniform distributions. Specifically, the distribution for each \( w_k \) is given as follows: \( w_k = a_k + (b_k - a_k)\nu_k \), where \( \nu \) is a draw from a standard Uniform distribution and where \( b_k - a_k \) gives the range of \( w_k \). We further note that the marginal WTP distributions are assumed to be independent. While this may be somewhat restrictive, it does not preclude us from exploring the issue at hand, namely the bounding of marginal WTP distributions to reflect the alternatives actually considered by respondents. Importantly, this also avoids the proliferation of parameters needed to represent class-specific diagonal and off-diagonal terms of the Cholesky matrix (cf. Campbell et al., 2013), making the model more parsimonious.

**3 Case-study: demand for assured, safe and traceable food**

This section starts with a general description of the empirical case-study. Then we discuss the experimental design procedure used to generate the choice tasks, which we follow with an outline of the survey implementation and data collection.

**3.1 Stated choice experiment for value-added food products**

Increasingly, food safety legislation is focusing on ensuring safety and traceability of food from ‘farm-to-fork’. Connected with this, the use of various labelling policies as a method of ensuring integrity in the food chain and enhanced consumer confidence is becoming more widespread. In addition to the obvious health benefits of ensuring food safety, there are numerous economic benefits that can be achieved. One such economic benefit is the value-added to food products through additional features, such as country of origin labelling and safety assurance labels (cf. Hu et al., 2012; Martínez et al., 2011, for recent stated preference studies looking at food labelling).

In this paper, we apply our methodology to the data used in Campbell and Doherty (2013) and Doherty and Campbell (2013). Specifically, the case-study explored the WTP for value-added services to chicken meat, specifically, two uncooked chicken breasts. To identify the relevant food safety attributes and levels associated with this chicken product, the study design was informed by expert opinion from food scientists involved in developing methods to verify the safety and authenticity of food. Although these discussions helped establish the attributes of interest, we gathered information from food stores and undertook a series of focus group discussions with members of the general public and pilot surveying to

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4 Although, see Doherty et al. (2012) for application using a mixture of two continuous distributions.
further ensure that the attributes and levels used to describe the product alternatives in the experiment were understandable and relevant to the general public.

Following this, three main food safety attributes were identified: (i) food testing standards; (ii) traceability standards; and, (iii) animal health/welfare standards. All three of these value-added services were defined as having two standards: (i) an enhanced standard; and, (ii) a current standard. For food testing, the enhanced standard represented the use of additional testing to ensure safer food. For traceability, the enhanced standard consisted of the use of technology to verify the exact origins of the meat so that labelling fraud could not occur. For the animal health/welfare attribute, respondents were informed that the enhanced standard tested the animals for the presence of any drugs or diseases, whilst the current standard only tested for the presence of drugs. A region of origin attribute was also included to decipher preferences for chicken produced within the British Isles versus chicken products that came from outside this area. Price was the final attribute included to explore sensitivity to income loss for the purchase. The price attribute, which was reflective of supermarket prices, varied over six levels, ranging between £2.00 and £4.50 in £0.50 increments.

3.2 Experimental design

Having established the attributes and their levels, in an attempt to maximise sampling efficiency and account for the uncertainty with regard to the assumed parameter values, a Bayesian efficient experimental design was generated, based on the minimisation of the $D_B$-error criterion (for a general overview of efficient experimental design literature, see e.g., Scarpa and Rose, 2008, and references cited therein). Our prior parameter estimates were informed on the basis of initial estimations produced from a MNL model on our pilot study of 400 observations (gathered from 50 respondents). We also used the feedback from the expert opinions, focus group discussions as well as evidence from the literature to help define the random priors and to establish the appropriate number of tasks that should be used in the final design.

The final design comprised of 16 choices, which were blocked into two smaller designs, such that each respondent completed a panel of eight choice tasks and a complete design was obtained every two respondents. For each task, respondents were asked to choose between two experimentally designed alternatives and a ‘buy none’ option. When making their choices, respondents were asked to consider only the information presented in the choice task and to treat each task separately.

3.3 Survey implementation and data collection

The choice data was collected during September 2010 via an on-line survey. In total, we recruited 622 respondents residing in Great Britain resulting in 4,976 observations for model estimation. The sample consisted of approximately equal numbers of male (49 per cent) and female (51 per cent) respondents, which is comparable to the national population statistics. In accordance with the regional breakdown, 86 per cent, 9 per cent and 5 per cent of respondents resided in England, Scotland and Wales, respectively. Also in line with the breakdown of the adult population of Great Britain, the majority of respondents were younger than 45 years (69 per cent) and worked, either on a full-time or part-time basis (63 per cent). Of the 51 per cent of respondents who disclosed their income, the average annual gross income was almost £28,000, which is also comparable with national statistics.

4 Results

We begin this section with the results obtained from the discrete choice models outlined in Section 2. Following this, we compare the marginal WTP distributions obtained under the different model assumptions.

4.1 Estimation results

Estimation results are presented in Table 1. As a point of reference our analysis starts with the MNL model, with a parameter for price/scale (denoted by $\alpha$); marginal WTP parameters for the value-added services$^5$; and, a marginal WTP for either chicken product compared to the ‘buy none’ option, whose

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$^5$The value-added service attributes are entered as dummy variables, with the value of one representing the enhanced standard for the three food safety attributes and chicken that has been produced within the British Isles in the case of the region of origin attribute.
Table 1: Estimation results

<table>
<thead>
<tr>
<th>Variable</th>
<th>MNL</th>
<th>LC-IAL</th>
<th>RPL&lt;sup&gt;a&lt;/sup&gt;</th>
<th>LC-RPL-IAL&lt;sup&gt;a&lt;/sup&gt;</th>
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<td></td>
<td>est.</td>
<td>[t-rat.]</td>
<td>est.</td>
<td>[t-rat.]</td>
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<tr>
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<td>est.</td>
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<td>[t-rat.]</td>
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<td>[t-rat.]</td>
</tr>
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<td></td>
<td>est.</td>
<td>[t-rat.]</td>
<td>est.</td>
<td>[t-rat.]</td>
</tr>
<tr>
<td>Price/Scale</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>µ</td>
<td>-0.668</td>
<td>24.70</td>
<td>-0.677</td>
<td>23.90</td>
</tr>
<tr>
<td>σ</td>
<td>0.842</td>
<td>11.15</td>
<td>0.970</td>
<td>12.68</td>
</tr>
<tr>
<td>$a_{C_1}$</td>
<td>1.146</td>
<td>19.81</td>
<td>1.130</td>
<td>19.04</td>
</tr>
<tr>
<td>$a_{C_2}$</td>
<td>2.551</td>
<td>25.68</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>$a_{C_3}$</td>
<td>&lt;0.001</td>
<td>&lt;0.01</td>
<td>&lt;0.001</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Food testing</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>$a_{C_1}$</td>
<td>0.666</td>
<td>11.98</td>
<td>0.654</td>
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<tr>
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<td>3.29</td>
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<td>&lt;0.01</td>
<td>&lt;0.001</td>
<td>&lt;0.01</td>
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<tr>
<td>$a_{C_4}$</td>
<td>0.709</td>
<td>0.01</td>
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<tr>
<td>$a_{C_5}$</td>
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<td>&lt;0.001</td>
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<tr>
<td>$a_{C_6}$</td>
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<td>0.33</td>
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<tr>
<td>Traceability</td>
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<tr>
<td>$a_{C_1}$</td>
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<tr>
<td>$a_{C_3}$</td>
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<td>4.31</td>
<td>1.986</td>
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<td>Animal health/welfare</td>
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<td></td>
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<tr>
<td>$a_{C_1}$</td>
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<td>4.06</td>
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<td>0.44</td>
<td>0.373</td>
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<tr>
<td>$a_{C_3}$</td>
<td>0.554</td>
<td>0.88</td>
<td>0.679</td>
<td>0.90</td>
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<tr>
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<td></td>
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<tr>
<td>$a_{C_1}$</td>
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<td>&lt;0.01</td>
<td>&lt;0.001</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>$a_{C_2}$</td>
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<td>&lt;0.01</td>
<td>&lt;0.001</td>
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<tr>
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Continued on next page
coefficient can be interpreted as the marginal WTP for the ‘standard’ or ‘baseline’ chicken product. In line with our expectations, we find that the marginal WTP coefficients for the three food safety attributes are all significant and estimated as having positive signs—implying that respondents are willing to pay a price premium for these value-added services. Comparing the magnitudes of these coefficients suggests that respondents place the highest value on chicken that has undergone enhanced food testing to ensure food safety (£1.15) and that the chicken was produced under enhanced animal health/welfare standards (£1.07). The ability to fully trace the chicken is predicted as having a considerably lower price premium (£0.67). Also, in accordance with prior expectations, the marginal WTP coefficient for the locally produced value-added service is found to be positive, and significant—revealing that respondents are more likely to purchase chicken breasts that are produced in the British Isles, compared to chicken produced elsewhere. Nevertheless, we find that the price premium respondents are willing to pay for locally produced chicken breasts (£0.28) is considerably lower than all of the food safety value-added services. As anticipated, respondents dislike the situation of not having any chicken breasts and are willing to pay almost £3.50 to obtain a ‘baseline’ chicken product (i.e., a chicken product with no value-added services and that has not been reared within the British Isles) compared to having none.

When aggregated, the marginal WTP estimate we arrive at is £6.63. This, therefore, represents the maximum marginal WTP for the ‘premium’ chicken product (i.e., a chicken product with all value-added services and that has been reared within the British Isles) versus buy none. On the face of it, this would imply that the all respondents have a maximum marginal WTP that is above the highest price level of £4.50, and that all alternatives (irrespective of their price level) were considered by respondents.

We now turn to the LC-IAL model, which accounted for cost thresholds and bounded marginal WTP estimates. The six different price levels (i.e., values between £2.00 and £4.50 in £0.50 increments) used to describe chicken products and the zero-priced ‘buy none’ alternative leads to a seven-class model:

**Class 1:** actual choice set included alternatives priced up to and including £4.50 (i.e., is the same as the set offered in the choice experiment);
Class 7: actual choice set is confined to the zero-priced ‘buy none’ alternative.

Although homogeneity within each WTP bound was not permitted, we acknowledge that the confounding between heterogeneity and processing makes it difficult to identify whether the latent classes reflect threshold behaviour or preference heterogeneity. We, nevertheless, feel this is justified, since it would seem illogical not to bound marginal WTP where it is believed that respondents only considered alternatives that lie within their cost threshold. This issue aside, the model results do suggest that the majority of respondents (89 per cent) considered all alternatives and have a total marginal WTP at least as high as the highest price level of £4.50.6

Given the large class size it is not surprising to find that marginal WTP estimates associated with this class are not dissimilar to those obtained from the MNL model. The only exception to this is the marginal WTP obtained for a baseline chicken product which is £1.40 higher to the estimate retrieved under the MNL model. Aggregating the marginal WTP estimates for this class, who did not eliminate any alternatives from their decision, gives £7.98. Of the remaining respondents, almost half (in total 5 per cent) are suggested to consider all alternatives apart from those priced £4.50. Interestingly, it would appear that this class would only consider buying chicken products that have undergone enhanced food safety testing, are traceable, and that have been reared within the British Isles. The aggregated marginal WTP estimate for this class is calculated to be £4.04, which is between the highest price level (£4.50) and the second highest price level (£4.00). For the remaining latent classes, the very small class sizes do not facilitate any meaningful interpretation. Notwithstanding this, we do draw attention to the fact that only 2 per cent of the respondents are predicted as having only considered the buy none alternative. This implies that there are very few serial non-participators in this sample (i.e., respondents who always select the buy none alternative (cf. von Haefen et al., 2005; Burton and Rigby, 2009)) and, importantly, it suggests that 98 per cent of respondents are willing to pay at least the lowest price level (£2.00) for the chicken product.

Comparing model fit reveals that the LC-IAL model is associated with an improvement of over 400 log-likelihood units compared to the MNL model. Importantly, looking at the $\hat{\rho}^2$ and information criteria indicates that this improvement is supported, even after accounting for the large number of additional parameters. Furthermore, we do recognise that the $\hat{\rho}^2$ and information criteria would have been even more convincing if we were to merge several of the smaller classes, and remove the many variables that were not statistically significant. We, nevertheless, decided to retain all possible consideration sets and to leave in insignificant variables, because we feel that it leads to a richer insight into the choice tasks that are actually considered by respondents and their marginal WTP. Besides, we are interested in segmenting respondents according to their decision-making process and marginal WTP bounds, which means that the usual information criteria used in latent class analysis is less relevant.

While the results of the LC-IAL model indirectly suggested heterogeneous marginal WTP estimates among the sample of respondents, the RPL model is intended to explicitly uncover this heterogeneity. In all cases, the lower bound of the Uniform marginal WTP distributions are essentially zero. The fact that the upper bounds of these distributions are all found to be significantly higher than the lower bound confirms the presence of heterogeneous marginal WTP. We remark the relatively high upper bound of £12.74 for the marginal WTP for a baseline chicken product. This means that the upper bound of the aggregate marginal WTP (which is bounded between £0.07–£18.70) is also quite high, as are the measures of central tendency (£9.39). Despite the increase in almost 200 log-likelihood units, the high marginal WTP values retrieved under this model cast doubt on its suitability.

Our final model, LC-RPL-IAL, attempts to account for cost thresholds and facilitates random variation in marginal WTP within the bounds implied by the respondent’s restricted choice set. We again find strong evidence that the majority (87 percent) of respondents considered all alternatives when making their decision. Within this class, we highlight the identification of heterogeneous marginal WTP only for the food testing and animal health/welfare value added services. The maximum marginal WTP for the ‘premium’ chicken product for this class is bounded between £5.52–£11.34, which, compared

6While this class dominance suggests that most respondents found the upper price level acceptable, we cannot rule out that it may be an artefact of ‘yeah-saying’ behaviour or some sort of strategic behaviour. Given this finding and with perfect hindsight it would have been helpful to have used a larger price range, so that further comparisons could be made.
to that implied under the RPL model, is considerably much more in-line with prior expectations. We also remark that the measures of central tendency associated with this class (£8.43) is also much lower compared to that predicted under the RPL model. Again, while the small class sizes do not permit a rigorous investigation of the parameters retrieved for the remaining classes, we draw attention to the fact that in these classes there is not strong evidence of class-specific heterogeneous marginal WTP. We, once more, recognise that this may be an artefact of confounding between heterogeneity and processing. Nevertheless, the fact that the model fit obtained under the LC-RPL-IAL model is almost 200 log-likelihood units higher compared to that associated with the LC-IAL model justifies the move to accommodating within class heterogeneity. Furthermore, this improvement in model fit is confirmed by the $\bar{\rho}^2$ and associated information criteria diagnostics. However, on the basis of model fit and other goodness-of-fit measures, the LC-RPL-IAL model would appear to be inferior to the RPL model. 7

However, given the unexpected high marginal WTP estimates retrieved under the RPL model and the fact that it has only a marginal inferior model fit, we favour the LC-RPL-IAL model on the basis of the much richer insight it provides.

### 4.2 Comparison of WTP

For a more detailed examination and sensitivity of the estimated marginal WTP distributions, in Table 2 we report summary statistics of these distributions under all four model specifications. For this, we generate unconditional marginal WTP distributions based on 10,000 simulated samples of 10,000 respondents.

All four models produce very similar central tendency statistics for the value-added and region of origin attributes. This aside, the most striking differences are the associated marginal WTP distributions for the baseline chicken product. Both the LC-IAL and LC-RPL-IAL models identify the realistic situation of a mass who would be willing to pay £0 for the baseline chicken product. Both the LC-IAL and LC-RPL-IAL models identify the realistic situation of a mass who would be willing to pay £0 for the baseline chicken product. The central tendency statistics of

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marginal WTP attained under the RPL model for the baseline chicken product are found to be of a higher magnitude, which reaffirms the repercussions of not accounting the actual consideration sets and WTP thresholds. Related to this finding, we remark that the upper tail for the baseline chicken marginal WTP distribution becomes less extreme as we move from the RPL model to the LC-RPL-IAL model. A similar pattern emerges for the aggregated marginal WTP for an ‘premium’ chicken product (i.e., a chicken product with all three value-added services and has been reared within the British Isles).

Methodological issues aside, we draw attention to the fact that the attributes only contribute a fraction of the value respondents assign to the ‘premium’ chicken product. A substantial proportion of the total value respondents place on this product is reflected by their marginal WTP for the baseline chicken product. Nonetheless, the value-added and region of origin attributes do contribute approximately 40 per cent of the maximum value respondents are willing to pay the chicken product. We do remark, however, that the majority of this is connected with the food testing and animal health/welfare value-added services.

5 Conclusion

In this paper, we explore the behavioural proposition that respondents may exhibit patterns of the use of thresholds and cut-offs to define their consideration set and disregard those alternatives that fall outside of their maximum WTP. We expand the independent availability logit model (similar in form to a latent class model, but where we define each class to describe a specific consideration set and endogenous WTP bound) to account for the complete range of cost thresholds that may be held by respondents. Additionally, we account for within class heterogeneity and use a WTP-space representation. A further feature is that the class-specific WTP distributions are truncated to be within the bounds deduced from the cost level(s) within each class-specific consideration set.

Results, based on a stated choice experiment exploring attributes of chicken products, provide confirmation that a relatively small share of respondents do not attend to all alternatives, and, in particular, restrict their ‘actual’ consideration set to only those that do not exceed their maximum WTP. Although, this is found to apply to only approximately 15 per cent of respondents, the repercussions on the estimated marginal WTP distributions are substantive—the marginal WTP distribution for a ‘premium’ chicken product is, on average, up to 20 per cent lower when actual consideration sets and WTP thresholds are accounted for. While specific to this dataset, this result highlights the problem of ignoring the fact that even a small proportion of respondents eliminate alternatives that exceed their maximum WTP. Our findings provide, what we feel is, compelling evidence for further research in this area. While we recognise the potential confounding issues with our approach, we feel that it does shed additional light on the manner in which respondents reach their final decision. This represents an important challenge for future studies.

References

Campbell, D., Vedel, S. E., Thorsen, B. J. and Jacobsen, J. B. (2013). Heterogeneity in the WTP for recreational access: distributional aspects, *Journal of Environmental Planning and Management* 0(0): 0–0.


