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Accommodating satisficing behavior in stated choice experiments☆

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Abstract

Accumulating evidence suggests that respondents in stated choice experiments use simplifying strategies. Such behavior is a deviation from random utility theory and can lead to wrong inferences regarding preferences. This is a first attempt to systematically explore satisficing in stated choice experiments. We consider 944 satisficing rules and allow respondents to revise the rules adopted throughout the choice sequence. Only a minority of respondents used the same satisficing rule across the entire sequence. Allowing for updating reveals that the use of the heuristic changes over the choice sequence. Considering satisficing behavior leads to improved model fits and different marginal willingness-to-pay estimates.

Keywords: random utility maximization, satisficing, stated choice experiments.

JEL codes: C25, D91, Q13.

1. Introduction

In a stated choice experiment an individual is often faced with a sequence of choice tasks containing several alternatives described by multiple attributes taking on a number of different levels. When analyzing such data, researchers assume that respondents choose the utility maximizing alternative in each choice task and consider and trade-off all aspects of every alternative (McFadden, 1974). However, individuals tend to fall back on simplifying heuristics and rules

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of thumb to manage better complex and difficult choice situations (Gigerenzer and Gaissmaier, 2011). Indeed, a growing body of research shows that respondents in stated choice experiments adopt a range of decision-making strategies and possible heuristics when making their choices (e.g., Swait and Adamowicz, 2001; Hensher, 2006; Hensher et al., 2012; Hess et al., 2012). Such behaviors represent deviations from random utility theory and is likely to lead to misguided inferences about individuals' preferences unless we can develop models to properly address the actual choice behavior. For example, a number of studies show that respondents ignore one or more of the attributes on a choice card (Hensher et al., 2005; Campbell et al., 2008, 2011; Scarpa et al., 2012; Sandorf et al., 2017), use lexicographic decision rules (Scott, 2002; Hess et al., 2010, 2012), eliminate- or select alternatives based on position or the levels of one or a few attributes (Tversky, 1972; Hess et al., 2012; Erdem et al., 2014; Campbell and Erdem, 2015) or minimize regret rather than maximize utility (Chorus et al., 2008; Thiene et al., 2012).

One of the fundamental basics of microeconomic theory is the problem of choice and the assumption of *homo economicus*, which describes the infinite ability of an individual to make utility maximizing choices with a full information set and complete knowledge of their preferences. Simon (1955) questions this idea and postulates that in real life situations individuals often do not have full information about all alternatives. Instead, alternatives are evaluated sequentially and searching for information and additional alternatives is costly. This might lead to individuals choosing an alternative that meets their aspiration level (i.e., an acceptable level of utility) instead of them continuing to search for the one that will maximize utility. This type of boundedly rational behavior is known as satisficing. Given the recent experimental evidence in the optimal search and choice process literature (see e.g. Caplin et al., 2011; Reutskaja et al., 2011; Stüttgen et al., 2012) that shows that individuals do indeed often make choices that are (partly) consistent with this heuristic, it is reasonable to consider if similar behavior is exhibited by respondents in stated choice experiments. For this reason, in this paper, we develop a model to identify and accommodate satisficers in the context of a stated choice experiment. To our knowledge this is the first attempt to systematically explore this issue in this context.

It is worth noting at this point that satisficing behavior is not necessarily sub-optimal, and in fact utility maximization (optimization) is a special case of satisficing (Tyson, 2008; Papi, 2012). Let us consider an individual facing a choice between different products in a store. We denote the complete set of alternatives (i.e., different products) by C. Furthermore, we assume that in this particular store individuals only have three products to choose between, $\langle x, y, z \rangle \in C$. The alternatives are presented sequentially, from left to right, and we assume an individual will evaluate each in that order and select the first one that meets or exceeds the satisficing criterion (reservation utility). Now, it is easy to see that if an individual satisfices, then the order in which alternatives are presented affects the obtained utility level. For example, if x maximizes utility and y meets the satisficing criterion, presenting the choice set in the following orders $\langle x, y, z \rangle$, $\langle x, z, y \rangle$ and $\langle z, x, y \rangle$ will all result in a utility maximizing choice. Any other combination of presenting the alternatives is likely to lead to sub-optimal choices.

Stated choice experiments are consistent with Lancastrian consumer theory in which a good is described in terms of its attributes and individuals derive utility from the attributes of a good rather than the good *per se* (Lancaster, 1966). In this case, the satisficing criterion can be at the attribute level in that certain attributes meet or exceed the aspiration level and this leads to the alternative being chosen. Furthermore, in stated choice experiments respondents typically make a sequence of choices. Simon (1955) points out that moving from a single choice situation to a sequence of choices might lead respondents to revise their satisficing criterion. This revision is likely linked to institutional and value learning as well as fatigue (e.g., Czajkowski et al., 2014; Campbell et al., 2015). It is not apparently clear *a priori* whether the aspiration level rises or falls throughout the sequence. For example, Krosnick (1991) thinks of optimizing and strong satisficing as two ends of a spectrum and that we move from left to right as fatigue sets in, meaning that we are more likely to observe satisficing behavior in the later choice tasks. On the other hand, it is possible that as a respondent progresses through the sequence of choice tasks they learn about the task and their preferences, which makes it easier to find satisfactory alternatives and the aspiration level increases to the point where choices are utility maximizing. Slightly different, but related, Simon (1955) argues that as the difficulty of finding satisfactory alternatives increases, the aspiration level falls, which suggests that satisficing should be more prominent when difficulty is high.

In this paper, we attempt to identify satisficers and accommodate such behavior using observed choices from a stated choice experiment. The actual satisficing criterion used by a respondent is unknown to the researcher, and accommodating all possible satisficing behaviors leads to a large number of criteria and reservation utilities. In this paper, we consider 944 possible satisficing criteria (reservation utilities) and make probabilistic statements about a respondent's use of the heuristic. As such, our paper represents a first attempt at systematically exploring satisficing behavior in a stated choice experiment setting. We use data from a stated choice experiment conducted in the Republic of Ireland aimed at eliciting willingness-to-pay for value-added services to uncooked chicken breast fillets. Our results show that, while the satisficing heuristic was indeed used by individuals in this dataset, only a minority exhibited this type of behavior throughout the sequence of choices. Breaking the sequence of choices into early and late choice tasks, as well as early, middle and late choice tasks, reveals that the use of the heuristic changes as an individual progresses through the sequence choices. However, we remark on the dilemma this creates, since detecting satisficing decision-making is much more difficult when fewer choice observations are used. This aside, we find convincing support that "rational" behavior is the dominant form of decision making, which reinforces the standard modeling assumption. Nevertheless, accommodating satisficing behavior significantly impacts model fit and marginal willingness-to-pay.

The remainder of the paper is structured as follows: in Section 2 we give a brief overview of previous work; Section 3 outlines the modeling approach; Section 4 presents the empirical case study; Section 5 discusses the results; and, in Section 6 we conclude and suggest a few avenues for future research.

2. Background

The concept of satisficing, and more broadly bounded rationality, has received much attention in the decades following Herbert Simon's seminal paper. The central idea is that individuals do not make optimal decisions with respect to some objective function (e.g., maximize utility), but rather make a decision based on some aspiration level of the objective function (e.g., a reservation utility)—a decision leading to an outcome that is "good enough" (Simon, 1955). An important aspect of the satisficing theory is that people do not have complete information about all available options. Indeed, Simon (1955) argues that information about options is received sequentially through a costly search process. In an early contribution to optimal search theory, Stigler (1961) makes the argument that the optimal amount of search for better options is such that the marginal cost of searching for one additional option is equal to the marginal expected gain from continuing to search, and furthermore that the expected gain is a decreasing function of the number of options seen. Intuitively, if an individual has already found a good option then the probability of finding one that is better is smaller, hence it might not be beneficial for the individual to continue searching. Radner (1975) takes these ideas one step further and focuses on three aspects of bounded rationality: (i) the existence of goals (aspiration levels); (ii) the search for improvement over the current situation; and, (iii) the long-run success of the decision. Specifically, he develops a model of satisficing in the context of effort allocation between activities, where an individual searches for improvements over the current allocation. If the current allocation does not meet the goals, then the individual will search for a new allocation of effort to achieve the goals. The stopping rule determining when the search ends and a new allocation is chosen is a function of past performance of effort allocation to the activities. Manski (2017) and Hey et al. (2017) are perhaps the most recent attempts to formalize the ideas of bounded rationality and satisficing as put forward by Simon (1955). Specifically, they frame the problem around a decision-maker who seeks to maximize a welfare function subject to a minimax-regret criterion. The decision-maker learns about the welfare function through costly deliberation. The model itself assumes that the decision-maker has three potential decision strategies: (i) a no deliberation strategy (e.g., choosing the first option in the choice set); (ii) a satisficing strategy where search costs are positive; and, (iii) an optimization strategy. The model applies to a class of models where the lower- and upper bounds of the welfare function are known to the decision-maker. Furthermore, in line with the ideas outlined by Simon (1955), if deliberation costs are prohibitively high a decision-maker will tend to use a "no deliberation" strategy, if they are sufficiently small he will likely use a satisficing strategy, and if they are very low, or possibly zero, he will use an optimizing strategy.

Recent experimental evidence shows that individuals make decisions that are (partly) consistent with the satisficing heuristic. For example, Caplin et al. (2011) develop an experiment with a real payment where individuals are asked to search through a list of options and select the one with the highest value. Each option was a simple arithmetic assignment. Through the experiment they track the choice process, with and without a time constraint, and find that subjects search through the options and select the first one meeting the aspiration level (reservation utility) from among the explored alternatives. Reutskaja et al. (2011), on the other hand, only find weak evidence of satisficing. They use eye-tracking to determine the search path, a strict time constraint and a monetary penalty for spending more than the allotted time searching, and find that respondents' choices among familiar snack items are only partly consistent with the satisficing heuristic. In a different eye-tracking study, Stüttgen et al. (2012) divides information search into "global", between alternative, and "local", within alternative, and use a modified hidden Markov model to determine probabilities of transitioning between the two states of information search, and when search is terminated and the choice is made. Their results support the hypothesis that respondents use a stopping rule consistent with the satisficing heuristic.

A relatively recent approach makes use of stochastic multi-criteria acceptability analysis to determine the most likely aspiration vector giving rise to an observed rank ordering of alternatives (Durbach, 2009). The resulting model is a type of "stochastic" satisficing model, where the initial aspiration vector is generated, and retained, in a Monte Carlo experiment if it fits the observed rank order of alternatives. The goal is to estimate a central aspiration vector such that it is consistent with the observed rank order of alternatives in the data. However, it is unclear how the search order affects the chosen aspiration vector and it appears that the ranking of all alternatives is considered when determining the aspiration vector. As such, the model captures an average minimum aspiration vector (reservation utility) across all individuals.

Dawes (1964) propose a similar heuristic to satisficing where an alternative is selected if all aspects of the alternative (e.g., attributes) meet a minimum level, which he termed a conjunctive choice heuristic. Building on this work, Grether and Wilde (1984) develop a conjunctive satisficing model, where the first alternative meeting the satisfactory level of all attributes is chosen. This model builds on the assumption that individuals have cut-off levels associated with acceptable/unacceptable attribute levels, which were elicited prior to the experiment. Swait (2001) extends this work and allows for "soft" cut-offs, where an individual could violate their pre-determined cut-offs by imposing a utility cost for doing so. The approach in this paper share some similarities with this strand of research, however, we do not elicit "cut-offs" nor do we rely on self-reported measures.

Another stream of research has focused on deriving axioms and provide axiomatic perspectives of the satisficing heuristic (Tyson, 2008; Caplin and Dean, 2011; Papi, 2012). These researchers attempt to derive "optimal" stopping rules under incomplete information search when the search order is fully or partially observed. For a good overview on recent contributions see Papi (2012).

Within the survey literature, the definition of satisficing has departed slightly from the original concept proposed by Simon (1955). This stream of research has focused more on satisficing as a pure simplification strategy to reduce choice task difficulty and increase completion times, and not necessarily to reach a satisfactory level of utility. Krosnick (1991) formulated a set of hypotheses which have guided research on satisficing in the survey literature, specifically respondents are more likely to: (i) select the first reasonable response; (ii) choose the status-quo option (if available); (iii) non-differentiate on rating scales (e.g., always choose the mid-point); and (iv) do "mental coin-flipping" which would result in more random answers. It is argued that this type of satisficing is a function of task difficulty, individual characteristics (e.g., cognitive ability), respondent engagement and fatigue (Krosnick, 1991; Carson et al., 1994; Downes-Le Guin et al., 2012). For example, Holbrook et al. (2003) compare census data collected by telephone with traditional face-to-face interviews and test the hypotheses of Krosnick (1991). The results show that respondents who were surveyed by telephone were more likely to have no opinion, non-differentiate on rating scales and agree with any assertion regardless of its content (acquiescence). Downes-Le Guin et al. (2012) argue that satisficing is a function of survey engagement and suggest using trap questions (e.g., "for quality assurance purposes please select 'Strongly Agree' " (p. 11)), straight-lining behavior (i.e., non-differentiation on rating scales) and speeding as measures of satisficing. They hypothesize that more engaged survey participants are less likely to satisfice according to these criteria and test this across four different presentation styles (treatments). Their results show no difference between treatments in terms of engagement scores. The hypotheses proposed by Krosnick (1991) have also influenced the way satisficing has been identified within the stated preference literature. For example, Lindhjem and Navrud (2011) compare an online contingent valuation study on biodiversity protection plans with a face-to-face implementation. To identify potential satisficers they measure the share of "don't know" responses to the willingness-to-pay question and variance in the distribution of answers to the payment card. The latter is an example of non-differentiation. They conclude that there was no significant difference between samples in terms of potential satisficers. In a recent study, Gao et al. (2015) identifies potential satisficers using a validation question (trap question), where a respondent was asked to select a particular response to help improve data quality. To test for the impact of satisficers they estimate random parameter logit models in willingness-to-pay space for satisficers, non-satisficers and a pooled model, to capture the impact of these respondents. Their results suggest that the model estimated on the subgroup identified as non-satisficers had better model fit compared to the one estimated on satisficers alone, and that satisficers had significantly different willingness-to-pay and larger variances in the elicited willingness-to-pay measures.

3. Modeling approach

To introduce necessary notation, we start by specifying a utility function that is linear in the parameters, where the utility of the chosen alternative i for respondent n in choice situation t is depicted by:

$$U_{i_{nt}} = c_i + \boldsymbol{\beta}\mathbf{x}_{i_{nt}} + \varepsilon_{i_{nt}}, \tag{1}$$

where c_i is an alternative specific constant, $\boldsymbol{\beta}$ is the row vector of marginal utility parameters to be estimated, $\mathbf{x}_{i_{nt}}$ is the column vector of attributes and ε_{i_n} is an *i.i.d.* type I extreme value distributed error term with constant variance $\pi^2/6$. Given these assumptions and, importantly, the assumption that choices are driven by the maximization of the respondent's utility, the probability of the sequence of choices $\mathbf{y}_n = [i_{n1}, i_{n2}, \ldots, i_{nT}]$ can be estimated by the conventional multinomial logit model:

$$\Pr(\mathbf{y}_n|\mathbf{X}_n, \mathbf{c}, \boldsymbol{\beta}) = \prod_{t=1}^{T_n} \frac{\exp(c_i + \boldsymbol{\beta}\mathbf{x}_{i_{nt}})}{\sum_{j=1}^{J} \exp\left(c_j + \boldsymbol{\beta}\mathbf{x}_{j_{nt}}\right)}. \tag{2}$$

3.1. Addressing satisficing behavior

While the random utility maximization model described above is widely used, it fundamentally rests on the assumption of compensatory (indirect) utility functions. In other words, respondents carefully weigh all of the attributes and consider all alternatives, before making an informed choice. However, this is costly in terms of cognitive effort on behalf of the respondent and is at odds with the increasing evidence that this strict assumption may not always hold. Instead, it is often necessary to depart from this convenient assumption and allow for models that can capture boundedly rational behavior, and, as such, increase the model's capacity to accurately predict choices. In this paper we identify satisficers using observed choices in a stated choice experiment. Unlike optimal search experiments and choice process data (see e.g. Caplin et al., 2011; Caplin and Dean, 2011), stated choice experiments are not created with the purpose of accommodating satisficing behavior. This requires a few simplifying assumptions. First, the order in which alternatives are evaluated is unobserved. To overcome this, we assume that a respondent evaluates alternatives from left to right. This implies that an individual will consider the first alternative in full (i.e., all attributes and the corresponding levels) before moving on to consider the next alternative. Processing from left to right is consistent with evidence from eye-tracking studies (Rebollar et al., 2015; van der Laan et al., 2015), and the cultural practice of reading left to right.[1] Second, the reservation utilities are unobserved and likely to differ across respondents. Using the attribute levels we create a large number of aspiration vectors (reservation utilities/satisficing criteria), and make probabilistic statements with regard to the one describing the observed sequence of choices.[2] Third, we assume a stopping rule such that the first alternative encountered that meets or exceeds the reservation utility is chosen. Fourth,

[1] We, nevertheless, recognise that this is a strong assumption, as a robustness check, we, therefore, also conduct the equivalent analysis under the assumption that individuals evaluate the alternatives from right to left. We report these results in Appendix A.

[2] This idea is similar to that described in Durbach (2009), yet ours is cast in an expected utility framework and the vectors are not chosen stochastically, but systematically and tested.

we assume that respondents have "zero recall", meaning that they cannot go back and choose among already revealed alternatives. This final assumption is necessary to identify the model given that the search path is unobserved and that the stopping rule is defined as choosing the first alternative that meets or exceeds the aspiration levels. We elaborate more on the implications of our assumptions in Section 5.4. Under these assumptions we can formalize a satisficing modeling framework, which we detail below.

A respondent chooses the first alternative that meets their satisficing requirement, s, meaning that their choice probability under a given rule is depicted by:

$$\Pr(i_{nt}|\mathbf{x}_{i_{nt}}, s) = \begin{cases} 1 & \text{if alternative } i \text{ is the first alternative that meets respondent } n\text{'s} \\ & \text{satisficing requirement } s \text{ in choice situation } t; \\ 0 & \text{if otherwise.} \end{cases} \tag{3a}$$

Note that if none of the alternatives meet the respondent's satisficing requirement, then the respondent will choose 'none':

$$\Pr(i_{nt} = \text{'none'}|\mathbf{x}_{i_{nt}}, s) = \begin{cases} 1 & \text{if no alternative meets respondent } n\text{'s satisficing} \\ & \text{requirement } s \text{ in choice situation } t; \\ 0 & \text{if otherwise.} \end{cases} \tag{3b}$$

To consider heterogeneous satisficing criteria (reservation utilities), we denote the range of possible satisficing criteria by S and the probability of respondent n's sequence of choices conditional on satisficing criterion s as:

$$\Pr(\mathbf{y}_n|\mathbf{X}_n, s) = \prod_{t=1}^{T_n} \Pr(i_{nt}|\mathbf{x}_{i_{nt}}, s), \tag{4}$$

where T_n denotes the total number of choice tasks faced by respondent n. The overall choice probability can be obtained by allocating the full probability across all S satisficing rules and the random utility maximization model:

$$\Pr(\mathbf{y}_n|\mathbf{X}_n, \mathbf{c}, \boldsymbol{\beta}, S, \omega, \boldsymbol{\pi}) = \omega^{\mathrm{c}} \Pr(\mathbf{y}_n|\mathbf{X}_n, \mathbf{c}, \boldsymbol{\beta}) + \omega \sum_{s=1}^{S} \pi_s \Pr(\mathbf{y}_n|\mathbf{X}_n, s), \tag{5}$$

where ω (derived below) is the unconditional probability that at least one of the S satisficing rules have been adopted, $\omega^{c} = 1 - \omega$ (i.e., the complement) is, therefore, the unconditional probability that the random utility maximization model is the appropriate framework, and $\omega\pi_s$ (also derived below) is the unconditional probability associated with satisficing rule s. Since all respondents' choices can be checked against every satisficing condition, the average share of the sample (i.e., unconditional probability) who adopted this strategy can be established and, thus, it is not required to estimate the satisficing class probabilities. The derivation of these probabilities is achieved by first specifying a N-by-S matrix, $\mathbf{A}$, where each element a_{ns} denotes an indicator variable, which takes the value of 1 if the entire sequence of T_n choices made by respondent n obeys satisficing condition s and 0 otherwise (which is equivalent to $\Pr(\mathbf{y}_n|\mathbf{X}_n, s)$):

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1S} \\ a_{21} & a_{22} & \dots & a_{2S} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \dots & a_{NS} \end{bmatrix}. \tag{6a}$$

Next, define $\mathbf{B}$ as a N-by-N diagonal matrix:

$$\mathbf{B} = \begin{bmatrix} \sum_{s=1}^{S} a_{1s} & 0 & \dots & 0 \\ 0 & \sum_{s=1}^{S} a_{2s} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sum_{s=1}^{S} a_{Ns} \end{bmatrix}, \tag{6b}$$

where the diagonal elements denote the total number of the satisficing rules that are supported by respondent n's sequence of choices. Matrix multiplication of $\mathbf{B}^{+}$ (i.e., the pseudoinverse of $\mathbf{B}$) and $\mathbf{A}$ yields $\mathbf{C}$:

$$\mathbf{C} = \mathbf{B}^{+}\mathbf{A}. \tag{6c}$$

Matrix $\mathbf{C}$ is row standardized to create proportional weights in cases where respondent's choices adhere to an unequal number of satisficing rules. This ensures that all weights are between 0 and 1 and that, in the absence of information on their true behavior, equal probabilities are assigned to all satisficing rules that are consistent with respondent n's choices. Therefore, the column means of $\mathbf{C}$ provide the mean likelihood for each satisficing rule across all respondents and the unconditional probability for each S satisficing rule (conditional on satisficing) can be obtained using:

$$\boldsymbol{\pi} = \left(\sum_{n=1}^{N} \left[\sum_{n=1}^{N} c_{n1} \quad \sum_{n=1}^{N} c_{n2} \quad \ldots \quad \sum_{n=1}^{N} c_{nS} \right] \right)^{-1} \left[\sum_{n=1}^{N} c_{n1} \quad \sum_{n=1}^{N} c_{n2} \quad \ldots \quad \sum_{n=1}^{N} c_{nS} \right]. \tag{6d}$$

The unconditional probability of respondents adopting at least one satisficing condition, ω, is given by the proportion who adopt one or more conditions:

$$\omega = N^{-1} \sum_{n=1}^{N} [b_n \neq 0]. \tag{6e}$$

Under this approach, we refer to the value of ω as the unconditional probability that at least one satisficing rule has been adopted, since it represents the 'prior' probability that a randomly selected respondent will have used this decision-making strategy. Although this probability estimate is unconditional and, therefore, does not directly provide any information on the actual decision-making strategy employed by a given respondent, it reflects the fact that a respondent's actual decision-making process is unobserved and cannot be known with certainty. Similarly, the value of $\omega\pi_s$ denotes the prior probability that a respondent employed statisficing condition s. Crucially, we note that the unconditional probabilities generated in Eq. (6) are informative priors which come explicitly from the choice observations of the whole sample, which is consistent with standard latent class models and, importantly, ensures the model is computational since the full probability is allocated over the random utility maximization class and across all satisficing rules: $\omega^{c} + \omega \sum_{s=1}^{S} \pi_s = 1$. Moreover, if none of the respondent's choices meet any of the satisficing rules, $\omega = 0$ meaning that the choice probability is equivalent to the multinomial logit probability. We, again, emphasize that ω and the vector $\boldsymbol{\pi}$ are not free parameters to be estimated, as they are established by checking respondents' choices against the satisficing rules of interest, as detailed in Eq. (6). The alternative specific constants, $\mathbf{c}$, and the vector of marginal utilities, $\boldsymbol{\beta}$, are the only free parameters that need be estimated to maximize the log-likelihood function. As a result, there is no increase in the number of parameters to estimate.

3.2. Accounting for preference heterogeneity and changes in satisficing behavior

The specification outlined above assumes that all respondents who do not adopt a satisficing decision-making rule share the same preferences for the choice attributes. However, it is now widely acknowledged that models relying on the strict notion that the taste intensities for a given attribute are the same for all respondents tend to be inferior to those that facilitate heterogeneity in preferences (e.g., see Hensher and Greene, 2003, for a detailed discussion). Such (unobserved) preference heterogeneity can be accommodated by assuming random distributions. Rather than continuous random distributions, we opt for finite (discrete) distributions. The advantage of such a non-parametric latent class approach is that commonly used continuous distributions may be unsuitable for representing the distribution of preferences, especially in situations where there are spikes in the distribution. Finite distributions, instead, can provide greater flexibility and have practical appeal as the results can have more intuitive meaning than the parameter and moments of the distributions that are retrieved from continuous parametric distributions.

In a latent class context, the number of possible values for the parameter coefficients is finite. Therefore, latent class specifications are especially suited for identifying and accommodating segments of respondents based on their underlying preferences. As outlined in Campbell et al. (2011), this can be accommodated by estimating different vectors of marginal utilities parameters, $\mathbf{c}_q$ and $\boldsymbol{\beta}_q$, where $q = \{1, 2, \ldots, Q\}$. A respondent's true preferences cannot be known with certainty and, thus, remains latent. To work around this, based on observed choice behavior, the presence of each vector of parameters can be established up to a probability, with the full probability per respondent allocated across all Q classes. The unconditional probability of observing $\mathbf{c}_q$ and $\boldsymbol{\beta}_q$ is denoted by $\omega^{\mathrm{c}}\psi_q$, subject to $\sum_{q=1}^{Q} \psi_q = 1$, where ψ_q is the prior likelihood of competing marginal utilities being their actual marginal utilities conditional on random utility maximization decision-making. Adding this extra dimension, the probability of a sequence of choices can then be rewritten as:

$$\Pr\left(\mathbf{y}_n|\mathbf{X}_n, \mathbf{c}_q, \boldsymbol{\beta}_q, S, \omega, \boldsymbol{\pi}, Q, \boldsymbol{\psi}\right) = \omega^{\mathrm{c}} \sum_{q=1}^{Q} \psi_q \Pr\left(\mathbf{y}_n|\mathbf{X}_n, \mathbf{c}_q, \boldsymbol{\beta}_q\right) + \omega \sum_{s=1}^{S} \pi_s \Pr\left(\mathbf{y}_n|\mathbf{X}_n, s\right). \quad (7)$$

The aspiration level, which defines a satisfactory alternative, may change as a respondent progresses through the sequence of choice tasks. It seems reasonable to expect that as a respondent—in their exploration of the alternatives, attributes and attribute levels—finds it easy to discover satisfactory alternatives, their aspiration level rises; whereas, if the respondent finds it difficult to discover satisfactory alternatives, there is likely to be a fall in the aspiration level (Simon, 1955, p. 111). While this immediately suggests that the degree of satisficing behavior might be greater when the good under evaluation is relatively unknown and complex, it also supports the need to relax the strict condition that a respondent adheres to a specific satisficing condition over the entire choice sequence. Instead, it may be more appropriate to break the sequence into phases, as done in Campbell et al. (2015). We also consider this as part of the analysis.

4. Study design and data

In this paper, we apply our methodology to the data used in Campbell and Doherty (2013), Doherty and Campbell (2014) and Campbell et al. (2014). The case study explored willingness-to-pay for value-added services to uncooked chicken breast fillets, specifically, for a tray of two uncooked chicken breast fillets. Relevant attributes and the levels associated with the uncooked chicken breast fillets were informed by expert opinion from food scientists, information from food stores, focus group discussions with members of the general public and pilot surveys to further ensure that the attributes and levels used to describe the product alternatives in the experiment were understandable and relevant to the general public. Three food safety attributes were decided upon: (i) food testing standards; (ii) traceability standards; and, (iii) animal health/welfare standards. All three of these attributes were defined as having two levels: (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 labeling 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 included to decipher preferences for uncooked chicken breast fillets that originate from either the island of Ireland or Great Britain versus uncooked chicken breast fillets that originate from outside these regions. Price was the final attribute included to explore sensitivity to income loss for the purchase. The price attribute, which was reflective of the then current market prices, varied over six levels, ranging between €2.50 and €5.00 in €0.50 increments. All attributes and their respective levels are summarized in Table 1.

Having established the attributes and their levels, in an attempt to maximize sampling efficiency and account for the uncertainty with regard to the assumed parameter values, a Bayesian efficient experimental design was generated, based on the minimization of the D_b-error criterion (as discussed in Scarpa and Rose, 2008). The experimental design was optimized for a multinomial logit model using prior parameter estimates established from initial estimations produced from the pilot study. The stated choice experiment consisted of a panel of twelve choice tasks, and each respondent faced all twelve. To control for anchoring or focalism, eleven different versions were used, each of which had a different sequence of the choice tasks. For each task, respondents were asked to choose between two experimentally designed alternatives and a 'buy neither' option. While making their choices, respondents were informed that the uncooked chicken breast fillets were of a similar weight to those in the market. They were asked to consider only the information presented in the choice task and to treat each task separately. Respondents were also reminded about their budget constraint and that if they thought the alternatives were too expensive or if they did not normally buy uncooked chicken breast fillets they should simply choose the 'buy neither' option.

The choice data was collected in 2010 via an on-line survey. This paper utilizes the data obtained from a random sample of 343 respondents residing in the Republic of Ireland, resulting in 4,116 choice observations for model estimation.

Table 1. Attributes and attribute levels

	Testing	Traceability	Animal health/welfare	Region of origin	Price
Level 1	Current standard	Current standard	Current standard	Island of Ireland	€2.50
Level 2	Enhanced standard	Enhanced standard	Enhanced standard	British Isles	€3.00
Level 3				Other origin	€3.50
Level 4					€4.00
Level 5					€4.50
Level 6					€5.00

5. Results and implications

We begin this section with an examination of the satisficing rules adopted by respondents. Following this, we present results from our econometric models and show the implications for willingness-to-pay estimation.

5.1. Adoption of satisficing decision-making rules

As part of our analysis, we consider a number of satisficing conditions. For the three food safety attributes (food testing standards, traceability standards and animal health/welfare standards) we assume three rules per attribute: either respondents choose the first tray of two uncooked chicken breast fillets with the: (i) current standard; (ii) the enhanced standard; or, (iii) respondents do not use any rule for this attribute. For the region of origin attribute we consider five rules. Either respondents choose the first tray of uncooked chicken breast fillets originating from: (i) Ireland; (ii) Great Britain; (iii) Ireland or Great Britain; (iv) from outside Ireland and Great Britain; or (v) respondents do not apply any rule. For the price attribute, we assume seven satisficing conditions: respondents choose the first tray of uncooked chicken breast fillets that is priced in the range: (i) €2.50–3.00; (ii) €2.50–4.00; (iii) €2.50–5.00; (iv) €3.50–4.00; (v) €3.50–5.00; (vi) €4.50–5.00; or, (vii) respondents do not apply any rule. While other conditions for each attribute are possible, we already capture $S = 944$ (i.e., $(3 \times 3 \times 3 \times 5 \times 7) - 1$) possible satisficing decision-making rules, which we found to be sufficient to accommodate most (if not all) of the rules adopted by respondents.[3]

In Table 2, we summarize the unconditional probabilities (Eq. (6)) of adoption of satisficing rules by each attribute. From this table we see that only a minority of respondents' choices respected a satisficing rule over the whole sequence of twelve choice tasks. In fact, perhaps as few as 14 percent of respondents adopted at least one of the 944 satisficing decision-making strategies over the entire sequence. This said, there is a sizable share (over 8 percent) who consistently chose the first tray of uncooked chicken breast fillets that originates from Ireland. This signals a strong sense of nationalism and preference for Irish uncooked chicken and the fact that respondents found it easier to identify with the regional label (e.g., perhaps as simple

[3]The combination where respondents do not apply a rule for any attribute is subtracted, thus producing 944 satisficing rules where at least one condition is adhered to.

Table 2. Percentage of respondents' choices that obey satisficing conditions

	Tasks 1–12	Tasks 1–6	Tasks 7–12	Tasks 1–4	Tasks 5–8	Tasks 9–12
Testing						
Current standard	0.000	0.000	0.000	1.166	2.818	0.583
Enhanced standard	3.499	4.568	4.373	5.345	6.733	6.511
Traceability						
Current standard	0.000	0.292	0.292	1.458	3.304	1.846
Enhanced standard	0.292	3.110	1.263	4.179	5.178	3.984
Animal health/welfare						
Current standard	0.000	0.292	0.292	2.138	2.624	0.583
Enhanced standard	0.583	0.875	0.875	2.915	6.414	3.790
Region of origin						
Ireland	8.163	10.787	9.913	17.590	15.549	11.370
Great Britain	0.292	0.292	0.292	0.972	2.216	0.583
Ireland/Great Britain	0.292	3.984	9.135	7.444	6.297	12.634
Outside Ireland/Great Britain	0.000	0.000	0.000	2.332	0.000	0.292
Price						
€2.50–3.00	0.875	0.875	1.749	3.401	0.875	3.207
€2.50–4.00	0.000	1.312	4.373	4.898	6.433	4.373
€2.50–5.00	0.000	0.777	0.437	1.983	1.798	3.644
€3.50–4.00	0.000	0.000	0.583	0.000	0.437	1.263
€3.50–5.00	0.000	0.146	0.729	4.762	2.430	1.166
€4.50–5.00	0.000	0.000	0.000	0.292	2.457	0.146
Satisficing and random utility maximization decision-making						
ω	13.994	25.948	34.111	54.519	57.726	52.478
ω^c	86.006	74.052	65.889	45.481	42.274	47.522

mark of freshness) compared to the other features. There is also a share (approximately 3.5 percent) who routinely, over the twelve choice tasks, chose the first tray of uncooked chicken breast fillets with enhanced testing to ensure safer food. None of the remaining satisficing rules were systematically adopted by any more than 1 percent of respondents over the entire choice sequence.

While, of course, we cannot be certain that these respondents used such decision-making strategies, the fact that the same behavior is respected over a sequence of twelve choices is convincing, making it difficult to dismiss. Obviously, the longer the sequence of choices, the more confidence we can have that a particular rule was adopted. However, because aspiration levels (Simon, 1955) may change due to learning and fatigue (Campbell et al., 2015) as a respondent progresses through the sequence of choice tasks, it is also of interest to explore the incidence of satisficing behavior at different stages in the choice sequence. For this reason, in Table 2, we also report the unconditional shares obtained when the sequence is broken into stages.

As would be expected, relaxing the condition that a satisficing rule is implemented in all choices means that more rules are detected. Comparing the first and last six choice tasks reveals that over one-quarter and one-third of respondents, respectively, obeyed at least one of the 944 satisficing rules. Interestingly, this suggests that this particular type of satisficing is more prevalent in the latter stages of the choice sequence. This result makes intuitive sense. As a respondent moves through the choice sequence fatigue sets in and adopting a satisficing rule may be a conscious decision. Again, we find strong evidence, both in early and latter stages of the choice sequence, that respondents select the first alternative originating from Ireland. This said, respondents appear to relax their decision-rules as they progress through the stated choice experiment as there is a large increase (from 4 percent to 9 percent) in respondents who do not distinguish between uncooked chicken breast fillets produced in Ireland and Great Britain. We also draw attention to the fact that there is a discernible increase in respondents' sensitivity to cost in the latter six choices, as evident by the increased share of respondents using a satisficing rule based on the lowest price levels. When we compare equivalent shares for the first four, middle four and last four choice tasks, these differences are even more apparent. In particular, 55, 58 and 52 percent of the choices in these sub-panels, respectively, comply with at least one satisficing rule. However, it is noted that our ability to identify satisficing rules is reduced with these shorter sub-panels. For obvious reasons, we refrain from breaking the choice sequence any finer.

5.2. Estimation results

In this section, we present results from various models to ascertain the impact of the satisficing heuristic on elicited preferences. Table 3 reports estimation results obtained from different specifications. Models are estimated under the assumption of random utility theory and a combination of random utility theory and satisficing behavior, where satisficing is measured at the panel level and different sub-panel levels to allow for situations where respondents revise their satisficing criterion as they progress through the choice tasks. We further present results from models in which preference homogeneity is assumed and models in which preference heterogeneity is addressed.

First, we focus on the preference homogeneity models in Table 3(a) and, as a point of reference, we take the multinomial logit model (Model 1). In line with *a priori* expectations, the marginal utility parameters for the three food safety attributes are positive and significant, implying that respondents prefer enhanced standards compared to the current standards. Com-

Table 3. Estimation results

(a) Multinomial logit models

	Model 1		Model 2		Model 3		Model 4	
β_{Testing}	0.466***	(0.050)	0.402***	(0.047)	0.423***	(0.050)	0.500***	(0.060)
$\beta_{\text{Traceability}}$	0.261***	(0.050)	0.269***	(0.052)	0.278***	(0.054)	0.293***	(0.062)
$\beta_{\text{Animal health/welfare}}$	0.378***	(0.047)	0.399***	(0.050)	0.450***	(0.058)	0.466***	(0.067)
β_{Ireland}	1.049***	(0.087)	0.921***	(0.087)	0.894***	(0.092)	0.779***	(0.112)
$\beta_{\text{Great Britain}}$	0.166***	(0.061)	0.208***	(0.065)	0.207***	(0.071)	0.098*	(0.076)
β_{Price}	-0.425***	(0.041)	-0.475***	(0.045)	-0.455***	(0.049)	-0.545***	(0.058)
$c_{j=1}$	0.018	(0.033)	0.018	(0.036)	-0.039	(0.040)	-0.179***	(0.045)
$c_{j=\text{none}}$	-1.884***	(0.204)	-2.297***	(0.234)	-2.239***	(0.250)	-2.748***	(0.287)
Log-likelihood	-3,553.479		-3,223.231		-3,259.894		-3,357.534	

Notes: All models include 4,116 choice observations. All estimated standard errors (in parentheses) are robust and clustered at the respondent level. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent level respectively using the p-value of a one-sided test.

(b) Latent class models

	Model 5		Model 6		Model 7		Model 8	
Preference class 1								
β_{Testing}	0.468***	(0.055)	0.389***	(0.050)	0.420***	(0.055)	0.500***	(0.068)
$\beta_{\text{Traceability}}$	0.294***	(0.054)	0.290***	(0.055)	0.303***	(0.057)	0.327***	(0.067)
$\beta_{\text{Animal health/welfare}}$	0.425***	(0.053)	0.436***	(0.055)	0.490***	(0.063)	0.531***	(0.077)
β_{Ireland}	0.699***	(0.086)	0.796***	(0.095)	0.822***	(0.098)	0.733***	(0.124)
$\beta_{\text{Great Britain}}$	0.204***	(0.070)	0.223***	(0.072)	0.250***	(0.074)	0.119*	(0.080)
β_{Price}	-0.479***	(0.051)	-0.520***	(0.054)	-0.491***	(0.056)	-0.568***	(0.069)
$c_{j=1}$	0.030	(0.036)	0.026	(0.038)	-0.046	(0.041)	-0.167***	(0.047)
$c_{j=\text{none}}$	-3.481***	(0.263)	-3.699***	(0.309)	-3.946***	(0.253)	-4.387***	(0.450)
$\psi_{q=1}$	0.806***	(0.050)	0.878***	(0.058)	0.865***	(0.057)	0.886***	(0.069)
Preference class 2								
β_{Testing}	0.869***	(0.237)	1.397***	(0.554)	1.227***	(0.249)	1.413***	(0.398)
$\beta_{\text{Traceability}}$	0.437**	(0.251)	0.324*	(0.245)	0.136	(0.240)	0.609**	(0.326)
$\beta_{\text{Animal health/welfare}}$	0.447**	(0.248)	0.532*	(0.340)	0.446**	(0.220)	0.210	(0.415)
β_{Ireland}	5.204***	(1.428)	3.787***	(1.053)	2.382***	(0.392)	2.670***	(0.556)
$\beta_{\text{Great Britain}}$	1.287	(1.274)	1.161	(1.189)	-0.032	(0.449)	0.887*	(0.653)
β_{Price}	-0.406***	(0.153)	-0.371**	(0.213)	-0.626***	(0.139)	-0.840***	(0.222)
$c_{j=1}$	-0.008	(0.133)	-0.159	(0.276)	0.175	(0.240)	-0.443*	(0.301)
$c_{j=\text{none}}$	3.356**	(2.011)	3.353**	(1.876)	1.151*	(0.845)	1.152**	(0.675)
$\psi_{q=2}$	0.194***	(0.026)	0.122***	(0.029)	0.135***	(0.021)	0.114***	(0.025)
Log-likelihood	-3,014.303		-2,824.436		-2,962.901		-3,151.145	

Notes: All models include 4,116 choice observations. All estimated standard errors (in parentheses) are robust and clustered at the respondent level. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent level respectively using the p-value of a one-sided test.

paring the relative magnitudes of these coefficients suggests that respondents place the highest value on uncooked chicken breast fillets that have undergone enhanced food testing to ensure food safety and that the chicken was produced under enhanced animal health/welfare standards, whereas the ability to fully trace the origin of the uncooked chicken breast fillets is predicted as having considerable lower importance. In accordance with prior expectations, the marginal utility for locally produced uncooked chicken breast fillets is also found to be positive and significant—revealing that respondents are more likely to purchase uncooked chicken breast fillets originating from Ireland, relative to those from Great Britain and elsewhere (baseline level). Overall, this suggests that people have positive preferences for the value-added services considered here. As expected, the cost coefficient is negative and significant—indicating that, all else held constant, respondents are more likely to choose a cheaper tray of uncooked chicken breast fillets compared to one that is more expensive. In addition, we estimate alternative specific constants for the first and the 'buy neither' option: whose coefficients can be interpreted as the marginal (dis-)utilities relative to the second (or middle) alternative in the choice task. Only the 'buy neither' alternative specific constant is significant and its negative sign reveals that, on average, the sample of respondents dislike the situation of not having any uncooked chicken breast fillets.

Moving to the results obtained for Model 2, the second preference homogeneity model, which accommodates satisficing over the entire sequence of choices, we see that the signs and significance of the marginal utility parameters remain unchanged. We note that this is not surprising given that the majority (86 percent) did not consistently adopt a satisficing rule over the twelve choice tasks. Nevertheless, we draw attention to the huge improvement in model fit compared to the baseline model (an increase by over 330 log-likelihood units). However, we do acknowledge that this improvement is partly due to the fact that in this model we account for the panel nature of the data, which makes it difficult to attribute the gain in model fit purely to considering satisficing behavior. In Model 3 we recognize that the satisficing criterion used in the early choices may be different to the criterion used in latter choices. However, based on the log-likelihood there appears to be little support for this, since Model 2 has a superior fit relative to Model 3. This could be because with a longer panel we can obtain a 'cleaner' measure of satisficing behavior since we have greater confidence that what we are detecting is actually satisficing behavior. Therefore, we might expect to see a worsening in model fit, even though respondents change their decision rule. This gives rise to a dilemma: while segmenting the panel into finer sub-panels gives greater flexibility to capture potential changes in satisficing behavior as respondents progress through the choice sequence, the ability to determine satisficing behavior is reduced. This issue aside, we remark that, with the sole exception of the alternative specific constant for the first alternative, the parameters in Model 3 are all estimated as having the same sign and comparable statistical significance as those already discussed. The final preference homogeneity model, Model 4, is estimated on the basis that respondents used a different satisficing rule during the first four, middle four and last four choice tasks. We remark that this produces relatively similar parameter estimates but with some notable changes in statistical significance (especially those associated with the Great Britain level and the alternative specific constant for the first alternative). Interestingly, this model is associated with an inferior fit compared to the other models that recognize satisficing and assume preference homogeneity. This further reinforces the reduced ability to identify satisficing behavior using responses for a only few choice tasks.

Overall, accommodating for satisficing behavior leads to improved model fit. Across all preference homogeneity models, we see that respondents, on average, have a strong preference for uncooked chicken breast fillets originating from Ireland, which corroborates the results that a large proportion of the respondents that exhibited satisficing behavior used this criterion as a basis for their decision rule. Remark, however, that accounting for this type of behavior has led to a relative drop in the magnitude of the marginal utility parameter associated with Irish uncooked chicken breast fillets. While not surprising, it does signal the potential repercussions of overlooking satisficing behavior. Furthermore, we observe that the alternative specific constant for the first alternative is insignificant in Models 1–3, indicating that, on average, this option was not chosen more often relative to the second alternative holding all else constant. This reinforces the notion that the first option meeting the satisficing criterion is chosen and not the first alternative encountered. Retrieving a positive constant for the first alternative in Model 1, where satisficing is not accommodated, is especially important as it gives a signal of satisficing behavior. Admittedly, however, we do not find this constant to be significant, which, we suspect, reflects the small proportion of respondents satisficing as well as the small number of alternatives.

As noted earlier, because the assumption of preference homogeneity is unlikely to hold, we allow for heterogeneity using discrete distributions. In Table 3(b) we show the results of this analysis using two latent classes (i.e., two support points for the distribution of preferences).[4] An inspection of these models reveals that accommodating preference heterogeneity in this manner leads to improved model fit. Across all latent class models, there is an apparent large class of respondents, which—using the unconditional class membership estimate as a guideline—represents over 80 percent of respondents who made their decisions using a random utility maximization rule. The marginal utility parameters retrieved for this larger preference class bear relative resemblance to those obtained under the preference homogeneity models: positive (and significant) signs for the three food safety attributes and similarly for locally produced uncooked chicken breast fillets (albeit, with the relative differences in estimated coefficients for the Ireland and Great Britain regional labels being of a considerably smaller magnitude); and, negative (and significant) marginal utilities for the price attribute and the alternative specific constant for 'buy neither'. We observe that the second preference class is especially characterized by respondents who have a very strong preference for uncooked chicken breast fillets originating from Ireland and Great Britain. However, the most striking difference between the classes is the positive alternative specific constant for the 'buy none' option obtained in the second class—implying that respondents in this class would rather go without uncooked chicken breast fillets. Both classes strongly prefer uncooked chicken breast fillets originating from Ireland, which supports our previous finding that this is likely to be the main satisficing criterion applied by respondents in our dataset.

The best fitting model among the preference heterogeneity models is Model 6, which is the one that considers the same satisficing criterion (or criteria) is applied over the entire sequence of choices. While this reaffirms the difficulty in accurately identifying satisficing behavior with

[4]We acknowledge that two latent classes may not fully describe the preference heterogeneity and that further testing of hypothesis on the number of classes and model specification would lead to improvements in model fit. We justify our model choice on the grounds that adding further complexity might draw attention away from the main focus of the paper, namely the accommodation of satisficing behavior.

shorter sub-panels, of even greater importance is the large difference in fit between Models 5 and 6 (a difference of almost 200 log-likelihood units). Although in the preference homogeneity case we could not directly compare the improvement in model fit, in this case we can compare because they both explicitly account for the panel nature of the data. Therefore, this gives a very strong signal that we can reject the null hypothesis that all respondents made their choices in accordance with a utility maximizing rule, whereby they considered and traded-off between all aspects of all alternatives throughout the choice sequence. Aside from the improvements in model fit gained by recognizing and addressing satisficing behavior, we, once more, observe that it has implications for the retrieved marginal utility parameters, most notably in the smaller preference class where many of the attribute levels are no longer estimated as being significant.

5.3. *Welfare implications*

Any meaningful comparison of marginal utility parameters obtained under the various models is not possible, since each model is subject to a different scaling. What does make comparative sense are the implied marginal willingness-to-pay estimates, since the scale effect is neutralized. In Table 4, we compare the marginal willingness-to-pay estimates derived from each model.

Inspecting the marginal willingness-to-pay estimates obtained from the first preference homogeneity model in Table 4(a) reveals that, on average, the respondents are willing to pay a price premium of €2.50 per tray of two uncooked chicken breast fillets if the chicken originates from Ireland, compared to €1.11 for the equivalent tray that has undergone enhanced food testing, €0.90 per tray produced under enhanced animal health/welfare standards, €0.62 for two fully traceable uncooked chicken breast fillets and €0.40 per tray originating from Great Britain. Of central importance to this paper is the unmistakable change in marginal willingness-to-pay as one moves from the models that assume strict adherence to random utility theory.[5] Most noteworthy is the downward shift in value associated with uncooked chicken breast fillets orig-

[5]Though we note direct comparison is made difficult by the fact that the marginal willingness-to-pay estimates derived from the models that accommodate satisficing choice behavior are based only on the random utility maximization parameters. While marginal rates of substitution can be calculated from the estimated parameters at the level of the sampled population, they are not computable for individual respondents who adopt a satisficing rule since they do not make trade-offs between the attributes. This means that no relative implicit price can be computed for these respondents.

Table 4. Marginal willingness-to-pay (€ per tray of two uncooked chicken breast fillets) (95% confidence intervals in parentheses)

(a) Multinomial logit models

	Model 1	Model 2	Model 3	Model 4
Testing	1.11 (0.83–1.44)	0.85 (0.64–1.10)	0.94 (0.69–1.24)	0.93 (0.69–1.21)
Traceability	0.62 (0.38–0.88)	0.57 (0.35–0.81)	0.62 (0.38–0.88)	0.54 (0.32–0.78)
Animal health/welfare	0.89 (0.67–1.15)	0.85 (0.64–1.08)	1.00 (0.74–1.30)	0.86 (0.62–1.14)
Ireland	2.50 (1.92–3.22)	1.96 (1.49–2.53)	1.99 (1.47–2.63)	1.45 (0.99–2.00)
Great Britain	0.40 (0.10–0.73)	0.44 (0.17–0.76)	0.46 (0.15–0.82)	0.18 (-0.09–0.48)

Note: The Krinsky and Robb (1986) simulation technique (using 100,000 draws) was employed to generate the empirical distributions of marginal willingness-to-pay. Correspondingly, the lower and upper limits of the 95% confidence interval are given by the 2,501th and 97,500th sorted estimates of marginal willingness-to-pay.

(b) Latent class models

	Model 5	Model 6	Model 7	Model 8
Preference class 1				
Testing	0.99 (0.73–1.30)	0.75 (0.55–0.99)	0.86 (0.62–1.15)	0.89 (0.63–1.20)
Traceability	0.62 (0.39–0.87)	0.56 (0.35–0.79)	0.62 (0.39–0.88)	0.58 (0.35–0.84)
Animal health/welfare	0.89 (0.67–1.15)	0.84 (0.64–1.08)	1.01 (0.75–1.31)	0.94 (0.69–1.24)
Ireland	1.47 (1.04–2.00)	1.54 (1.13–2.05)	1.70 (1.22–2.29)	1.31 (0.84–1.88)
Great Britain	0.43 (0.13–0.78)	0.43 (0.15–0.75)	0.52 (0.20–0.88)	0.22 (-0.06–0.53)
Preference class 2				
Testing	2.66 (0.73–8.47)	1.03 (-21.58–36.73)	2.06 (1.14–3.50)	1.72 (1.00–2.68)
Traceability	1.48 (-0.15–6.09)	0.25 (-4.43–8.77)	0.26 (-0.51–1.24)	0.77 (-0.04–1.81)
Animal health/welfare	1.56 (-0.11–6.48)	0.11 (-9.64–16.29)	0.76 (0.02–1.80)	0.27 (-0.81–1.47)
Ireland	17.04 (3.40–63.49)	8.31 (-52.07–88.78)	4.08 (2.08–7.72)	3.42 (1.79–6.41)
Great Britain	4.94 (-2.27–26.58)	5.04 (-15.37–30.37)	0.01 (-1.39–1.76)	1.24 (-0.43–3.94)
Expected value				
Testing	1.30 (0.85–2.35)	0.71 (-1.16–4.48)	1.02 (0.74–1.39)	0.99 (0.71–1.31)
Traceability	0.78 (0.38–1.61)	0.52 (0.10–1.41)	0.57 (0.34–0.83)	0.60 (0.37–0.86)
Animal health/welfare	1.02 (0.61–1.87)	0.73 (-0.11–2.42)	0.97 (0.73–1.27)	0.87 (0.59–1.18)
Ireland	4.45 (1.69–12.80)	2.15 (-2.94–11.17)	2.02 (1.45–2.79)	1.56 (1.02–2.25)
Great Britain	1.29 (-0.21–5.28)	0.91 (-0.94–4.02)	0.45 (0.09–0.84)	0.34 (0.00–0.83)

Note: The Krinsky and Robb (1986) simulation technique (using 100,000 draws) was employed to generate the empirical distributions of marginal willingness-to-pay. Correspondingly, the lower and upper limits of the 95% confidence interval are given by the 2,501th and 97,500th sorted estimates of marginal willingness-to-pay.

inating from Ireland as well as those subject to enhanced testing. Referring back to Table 2, these were the attributes levels most commonly used as a satisficing rule. The importance of this result cannot be understated, since it purports marginal willingness-to-pay is sensitive to whether or not satisficing behavior is addressed. The way this behavioral heuristic is accommodated is also shown to be important, as evident from the differences in estimated marginal willingness-to-pay in Models 2–4.

Table 4(b) reports the marginal willingness-to-pay for the preference heterogeneity models. Results are given by latent class as well as a weighted average to facilitate more straightforward comparison. Scrutiny of the estimates obtained for each latent class shows a clear difference. In particular, we draw attention to the very high (and unrealistic) value of €17.04 respondents in the second (smaller) class are found to place on a tray of two Irish uncooked chicken breast fillets under Model 5. Crucially, as we move to Model 6, the equivalent value of €8.31 is much more plausible, which further corroborates the repercussions of not addressing satisficing for welfare analysis. Importantly, differences are also observed when comparing the expected values of marginal willingness-to-pay, the most apparent of which is when those obtained from the standard latent class model (Model 5) are compared against the best fitting satisficing model (Model 6). The naïve model produces expected values of marginal willingness-to-pay that are in the magnitude of between 1.4–2.1 times higher relative to the more reliable model that addresses satisficing.

5.4. Implications of our assumptions and limitations of our model

In order to infer satisficing behavior from stated choice data that was not designed to do so requires additional simplifying assumptions. Specifically, we made assumptions with respect to: i) left to right processing of alternatives; ii) unobserved reservation utilities; iii) the stopping rule (i.e., choosing the first alternative that meets or exceeds the reservation utilities); and, iv) that respondents have “zero recall”. Two of these require further discussion.

First, to overcome the problem that the sequence in which alternatives were evaluated (search path) was unobserved, we imposed the restriction that alternatives were processed from left to right. While this is a strong assumption it is consistent with evidence using eye-tracking and the persistent left-right bias often observed in stated choice experiments (Rebollar et al., 2015; van der Laan et al., 2015). Furthermore, we explicitly test the validity of this assumption by estimating the model as if respondents processed from right to left, the results of which are reported in Appendix A.[6] In our case, with only two experimentally designed alternatives, we obtain stronger evidence in favor of processing from left to right. However, we do recognize the inherent limitation in this assumption and that data which controls for the search path could provide further useful insights, including those that are vertically arranged, as in Campbell and Erdem (2015) and Sandorf et al. (2018).

[6]We thank reviewers for making this suggestion.

Second, we invoked the assumption that respondents have "zero recall", which means that they cannot go back and choose an already seen alternative. Admittedly, this is a strong assumption, and one that could be relaxed if we could track the alternative search path—for example, using eye-tracking. We argue that this assumption follows from the defined stopping rule. In the real world, it is possible that an individual would keep searching after having found a satisfactory alternative for confirmation and/or to see if they can find a superior alternative, but ultimately go back to a previously seen alternative. In our experiment, respondents were faced with two experimentally designed alternatives and a 'buy neither' option. If a respondent satisfices, we assume that they will choose the first alternative that meets or exceeds the reservation utility, and that this is true for the entire sequence (or sub-sequence) of choices. Under a given satisficing rule, where alternatives in a choice set are presented in the order A, B and C ('buy neither'), a respondent will choose: alternative A if it meets or exceeds the reservation utility; alternative B if it meets or exceeds the reservation utility *and* alternative A fails to do so; and, alternative C if neither alternatives A and B meet the reservation utility. If a respondent is observed to choose alternative A under a given satisficing rule, then we assume that no comparisons with alternatives B or C have been made. If a comparison with alternative B is made, then this would be (partly) captured by the random utility maximization model. If, on the other hand, alternative B is chosen, then that means that alternative A does not meet the reservation utility by definition. If a respondent has complete or incomplete recall and makes those comparisons, then it follows that our stopping rule is not binding. Instead, in the current modeling framework with only two experimentally designed alternatives, this type of comparison would be (partly) captured by the random utility maximization model. Furthermore, it is apparent that the "zero recall" assumption is not binding for the first alternative encountered. To summarize, while this assumption is rather strict and may be unlikely in a stated choice context with only three alternatives, where it is relatively easy for respondents look back and forth at alternatives, it follows from the stopping rule and is necessary for the identification of satisficing behavior in our modeling framework. The argument presented here for the three-alternative case can be extended to the multiple alternative cases, and relaxing this assumption requires information on the actual search path to modify the stopping rule.

As mentioned in the introduction, respondents in stated choice experiments may use a number of simplifying strategies and heuristics to better manage a difficult choice situation (see e.g. Hess et al., 2012). Failing to consider the actual choice process might lead to biased estimates and wrong inferences drawn with respect to preferences. As such, any applied model should reflect the researcher's beliefs about the underlying data generation process. For example, if we believe that people are utility maximizers, then a random parameter logit model with appropriately specified distributions might be a good choice, but if, on the other hand, we believe that people ignore attributes (Sandorf et al., 2017; Campbell et al., 2011); eliminate- or select alternatives based on the level of just one or a few attributes (Erdem et al., 2014); or satisfice, then we need to develop and use models that can capture and describe such behavior. Ideally, when we analyze data from stated choice experiments, especially in cases where the results are to be used for policy guidance, we should test a wide variety of models, including models that consider attribute non-attendance and elimination-by-aspects. The purpose of the current paper is not to derive estimates for policy nor to horse race models to see which describe the data generation process in this specific data set. Rather, we develop a model to capture satisficing behavior, which in our opinion, is an understudied choice heuristic in the context of stated choice experiments. At the end of the day, which model fits best in any given dataset remains an empirical question and will be entirely context dependent. Developing models that can accommodate a mixture of strategies will be interesting in the future, however, that might lead to models which are too closely tailored to the data.

6. Conclusions

In this paper, we explored respondent's use of satisficing choice behavior in the context of a stated choice experiment that was conducted in the Republic of Ireland to elicit preferences for value-added services to uncooked chicken breast fillets. The satisficing heuristic postulates that instead of choosing the alternative that maximizes utility, a respondent chooses the first one meeting their aspiration level. We assume respondents process alternatives from left to right and choose either according to standard random utility theory assumptions or use one or more of the 944 possible satisficing criteria we accommodate in our model.

First, we find that accounting for satisficing behavior leads to improved model fits relative to the models that fail to do so. We find that only a small proportion of respondents adopted a satisficing rule across the entire sequence of choices. A majority of respondents who adopted a satisficing heuristic chose the first alternative with uncooked chicken breast fillets originating from Ireland, suggesting a sense of nationalism and preference for Irish chicken. This result is corroborated by findings that the attribute for which respondents had the strongest preferences was indeed the region of origin. It has been suggested that in a sequence of choice tasks, respondents may revise their satisficing criterion in response to learning (e.g., it becomes easier/more difficult to find satisfactory alternatives) or fatigue. Consequently, we allow for respondents to update their satisficing rule throughout the sequence by first looking at early and late choice tasks, and second, looking at early, middle and late choice tasks. When we relax the assumption that the same criteria was used throughout the sequence, we find evidence that the use of the satisficing heuristic is consistent with the notion of learning and fatigue. Although we fully acknowledge the increased difficultly that this can pose for detecting satisficing decision-making.

Turning our attention to the estimates obtained for marginal willingness-to-pay, we find that failing to account for this type of behavior has a number of repercussions. The most important of which appears to be an overestimation of marginal willingness-to-pay, most notably for those levels most often used as a satisficing criterion. In fact, although it may only be a small subset of respondents who do not always adhere to the assumptions of random utility maximization, the key take home message is that the marginal willingness-to-pay estimates may be up to twice as high when satisficing is not addressed.

An obvious limitation to the current study is that the actual search path is unobserved, and that we only make probabilistic statements about the satisficing criteria employed under the assumption that alternatives are processed from left to right. While eye-tracking studies have been done within the context of a stated choice experiment (e.g., Balcombe et al., 2015; Krucien et al., 2017; Van Loo et al., 2018), to our knowledge this data has not been used to systematically explore satisficing. Re-examining existing eye-tracking studies and extending research in this direction could prove fruitful. Importantly, this will allow researchers to relax some of the limiting assumptions in the present model. We note that we find relatively few satisficers in our data. While this could be because relatively few respondents used this heuristic, it could also be caused by our design and assumptions. We believe that a larger number of alternatives in the choice tasks would lead to more people adopting a satisficing strategy. Increasing the number of alternatives will increase the complexity of the choice task and decrease the likelihood that all alternatives are considered. This represents an interesting and important extension to our work. In particular, if this could be combined with, for example, eye-tracking to enable modeling of the visual information search path. We noted earlier that if a respondent finds it difficult to discover satisfactory alternatives, the aspiration level falls (Simon, 1955), which suggests that this type of behavior should be more prominent when the good under consideration is unfamiliar and complex. Consequently, exploring satisficing in the context of, for example, environmental and public health goods is an interesting extension.

Appendix A: Satisficing based on a right to left processing strategy

The analysis in the paper assumed that respondents processed alternatives from left to right. However, with only a few alternatives per choice task, the opposite might be true, namely the processing of alternatives from right to left. Admittedly, this might have been the case in the present study since the 'buy neither' option was the rightmost alternative and may have formed a respondent's reference point.

We present the unconditional probabilities of satisficing rules by attribute under the assumption of right to left processing in Table A1. Only 9 percent of respondents are identified as having adopted at least satisficing rule over the entire choice sequence. The predominant rules over the twelve choice tasks are associated with enhanced testing, with approximately 3.5 percent of respondents who chose the first alternative with this attribute level. This is followed by chicken breast fillets originating from Ireland. Examination of the satisficing conditions observed for the first and last six choice tasks show that more satisficing rules are identified, with

Table A1. Percentage of respondents' choices that obey satisficing conditions (right to left)

	Tasks 1–12	Tasks 1–6	Tasks 7–12	Tasks 1–4	Tasks 5–8	Tasks 9–12
Testing						
Current standard	1.333	1.666	1.333	2.499	1.333	1.833
Enhanced standard	3.499	5.151	5.248	8.066	7.677	7.677
Traceability						
Current standard	1.333	1.666	1.333	2.499	1.333	1.833
Enhanced standard	0.292	3.499	1.166	5.123	5.470	5.659
Animal health/welfare						
Current standard	1.333	1.666	1.333	2.499	1.333	1.833
Enhanced standard	0.583	0.875	1.944	3.596	7.075	7.503
Region of origin						
Ireland	1.458	4.859	9.184	13.115	10.194	11.467
Great Britain	0.000	0.583	0.729	1.697	3.549	1.003
Ireland/Great Britain	0.000	6.317	2.177	9.286	5.180	3.752
Outside Ireland/Great Britain	0.000	0.389	0.466	1.846	2.235	0.617
Price						
€2.50–3.00	0.583	4.373	1.516	6.900	6.880	2.145
€2.50–4.00	0.000	2.818	3.265	7.337	8.455	6.391
€2.50–5.00	0.292	1.458	1.458	2.702	3.265	2.679
€3.50–4.00	0.000	0.292	0.583	2.138	2.284	7.138
€3.50–5.00	0.000	0.583	0.408	1.603	3.333	1.819
€4.50–5.00	0.000	0.194	0.700	1.069	5.714	1.366
Satisficing and random utility maximization decision-making						
ω	9.038	32.653	30.612	63.265	63.848	53.936
ω^c	90.962	67.347	69.388	36.735	36.152	46.064

almost one-third of respondents' choices obeying at least one rule in both phases. The first alternative with enhanced testing or that originates from Ireland are found to be most commonly chosen in both the early and latter stages of the choice sequence. This type of behavior is similarly observed when the sequence is broken down to the first four, middle four and last four choice tasks, but, as anticipated, with an increased share of respondents' choices obeying the satisficing conditions.

Importantly, referring back to Table 2, the percentage of respondents' choices found to obey satisficing based on right to left processing of alternatives is observed to be discernibly lower compared those identified using the left to right assumption. This suggests that left to right processing is more prevalent in this empirical setting. Although this finding, which is likely to be context-specific, corroborates our assumption in the main paper, there may be cases where right to left processing prevails meaning that consideration of different processing strategies is warranted.

In Table A2, we report the results based on right to left alternative processing. Focusing firstly on the preference homogeneity models in Table A2(a), we see that accounting for satisficing leads to improvements in model fit. Model 2, which assumes the same satisficing behavior is adhered to over the entire sequence of choice tasks, is, again, found to be the best performing among the multinomial logit models. Turning our attention to the latent class models in Table A2(b), we find similar support for accommodating satisficing behavior observed over the twelve choice tasks.

Overall, the estimated coefficients in Table A2 bear relative resemblance (in terms of sign and statistical significance) to those reported in Table 3. More noteworthy, however, is the fact that all models based on left to right satisficing rules are associated with a better model fit relative to their equivalent model assuming right to left processing. This critical insight gives a further signal that evaluating alternatives from left to right was more prevalent in this case study, thereby strengthening our decision to focus on left to right processing of alternatives in the main paper.

In terms of the implications for marginal willingness-to-pay estimation, Table A3 shows how accounting for right to left satisficing behavior leads to a general reduction in values. This

Table A2. Estimation results (right to left)

(a) Multinomial logit models

	Model 1	Model 2	Model 3	Model 4
β_{Testing}	0.466*** (0.050)	0.401*** (0.047)	0.380*** (0.050)	0.443*** (0.063)
$\beta_{\text{Traceability}}$	0.261*** (0.050)	0.249*** (0.051)	0.202*** (0.059)	0.138** (0.076)
$\beta_{\text{Animal health/welfare}}$	0.378*** (0.047)	0.389*** (0.050)	0.456*** (0.058)	0.313*** (0.073)
β_{Ireland}	1.049*** (0.087)	1.112*** (0.095)	1.131*** (0.106)	1.398*** (0.149)
$\beta_{\text{Great Britain}}$	0.166*** (0.061)	0.169*** (0.065)	0.088 (0.073)	0.039 (0.097)
β_{Price}	-0.425*** (0.041)	-0.471*** (0.044)	-0.463*** (0.048)	-0.503*** (0.063)
$c_{j=1}$	0.018 (0.033)	0.016 (0.034)	0.020 (0.038)	-0.024 (0.051)
$c_{j=\text{none}}$	-1.884*** (0.204)	-2.228*** (0.210)	-2.046*** (0.227)	-1.834*** (0.287)
Log-likelihood	-3,553.479	-3,282.876	-3,306.350	-3,387.489

Notes: All models include 4,116 choice observations. All estimated standard errors (in parentheses) are robust and clustered at the respondent level. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent level respectively using the p-value of a one-sided test.

(b) Latent class models

	Model 5	Model 6	Model 7	Model 8
Preference class 1				
β_{Testing}	0.468*** (0.055)	0.383*** (0.051)	0.343*** (0.058)	0.428*** (0.082)
$\beta_{\text{Traceability}}$	0.294*** (0.054)	0.272*** (0.055)	0.266*** (0.068)	0.303*** (0.111)
$\beta_{\text{Animal health/welfare}}$	0.425*** (0.053)	0.425*** (0.055)	0.507*** (0.068)	0.424*** (0.118)
β_{Ireland}	0.699*** (0.086)	0.717*** (0.087)	0.573*** (0.103)	0.561*** (0.157)
$\beta_{\text{Great Britain}}$	0.204*** (0.070)	0.220*** (0.071)	0.182** (0.086)	0.109 (0.120)
β_{Price}	-0.479*** (0.051)	-0.525*** (0.053)	-0.520*** (0.065)	-0.665*** (0.112)
$c_{j=1}$	0.030 (0.036)	0.028 (0.036)	0.014 (0.043)	-0.022 (0.055)
$c_{j=\text{none}}$	-3.481*** (0.263)	-3.591*** (0.232)	-3.722*** (0.345)	-3.476*** (0.375)
$\psi_{q=1}$	0.806*** (0.050)	0.814*** (0.051)	0.753*** (0.058)	0.729*** (0.077)
Preference class 2				
β_{Testing}	0.869*** (0.237)	1.331*** (0.333)	1.302*** (0.371)	2.276* (1.408)
$\beta_{\text{Traceability}}$	0.437** (0.251)	0.622*** (0.226)	0.201 (0.289)	0.073 (0.835)
$\beta_{\text{Animal health/welfare}}$	0.447** (0.248)	0.658*** (0.244)	0.574** (0.269)	0.522 (1.154)
β_{Ireland}	5.204*** (1.428)	5.964*** (0.870)	4.365*** (1.122)	6.318*** (0.965)
$\beta_{\text{Great Britain}}$	1.287 (1.274)	1.182 (0.959)	-0.384 (1.080)	-1.424 (1.406)
β_{Price}	-0.406*** (0.153)	-0.418*** (0.121)	-0.662** (0.303)	-0.527 (0.561)
$c_{j=1}$	-0.008 (0.133)	0.081 (0.189)	0.344* (0.262)	-0.295 (1.233)
$c_{j=\text{none}}$	3.356** (2.011)	3.619*** (0.994)	1.081 (2.218)	2.611** (1.433)
$\psi_{q=2}$	0.194*** (0.026)	0.186*** (0.025)	0.247*** (0.037)	0.271*** (0.047)
Log-likelihood	-3,014.303	-2,842.276	-2,991.644	-3,182.774

Notes: All models include 4,116 choice observations. All estimated standard errors (in parentheses) are robust and clustered at the respondent level. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent level respectively using the p-value of a one-sided test.

said, the downward shifts in value are of a lower magnitude compared to those witnessed when a left to right search path was assumed, as in Table 4.

Overall, this analysis gives more support to left to right processing of alternatives relative

Table A3. Marginal willingness-to-pay (€ per tray of two uncooked chicken breast fillets) (95% confidence intervals in parentheses) (right to left)

(a) Multinomial logit models

	Model 1	Model 2	Model 3	Model 4
Testing	1.11 (0.83–1.44)	0.86 (0.64–1.11)	0.83 (0.59–1.11)	0.89 (0.62–1.23)
Traceability	0.62 (0.38–0.88)	0.53 (0.31–0.77)	0.44 (0.19–0.71)	0.28 (-0.02–0.60)
Animal health/welfare	0.89 (0.67–1.15)	0.83 (0.62–1.06)	0.99 (0.74–1.28)	0.63 (0.34–0.94)
Ireland	2.50 (1.92–3.22)	2.38 (1.83–3.06)	2.47 (1.82–3.31)	2.84 (1.95–4.04)
Great Britain	0.40 (0.10–0.73)	0.36 (0.08–0.68)	0.20 (-0.12–0.55)	0.09 (-0.28–0.52)

Note: The Krinsky and Robb (1986) simulation technique (using 100,000 draws) was employed to generate the empirical distributions of marginal willingness-to-pay. Correspondingly, the lower and upper limits of the 95% confidence interval are given by the 2,501$^{\text{th}}$ and 97,500$^{\text{th}}$ sorted estimates of marginal willingness-to-pay.

(b) Latent class models

	Model 5	Model 6	Model 7	Model 8
Preference class 1				
Testing	0.99 (0.73–1.30)	0.74 (0.54–0.96)	0.67 (0.44–0.94)	0.67 (0.36–1.11)
Traceability	0.62 (0.39–0.87)	0.52 (0.32–0.74)	0.52 (0.25–0.83)	0.45 (0.16–0.72)
Animal health/welfare	0.89 (0.67–1.15)	0.82 (0.61–1.05)	0.99 (0.72–1.31)	0.67 (0.26–1.22)
Ireland	1.47 (1.04–2.00)	1.38 (1.00–1.85)	1.12 (0.68–1.66)	0.89 (0.32–1.75)
Great Britain	0.43 (0.13–0.78)	0.43 (0.15–0.74)	0.36 (0.02–0.76)	0.16 (-0.21–0.52)
Preference class 2				
Testing	2.66 (0.73–8.47)	3.50 (1.52–7.39)	2.45 (0.42–12.51)	3.97 (-60.34–63.06)
Traceability	1.48 (-0.15–6.09)	1.70 (0.38–4.25)	0.50 (-0.52–4.07)	-0.94 (-10.84–11.63)
Animal health/welfare	1.56 (-0.11–6.48)	1.83 (0.35–4.86)	1.10 (-0.04–6.63)	-0.49 (-26.26–26.31)
Ireland	17.04 (3.40–63.49)	16.20 (7.50–36.72)	8.63 (1.42–47.18)	9.37 (-116.24–127.46)
Great Britain	4.94 (-2.27–26.58)	3.52 (-1.39–12.94)	0.08 (-2.41–10.72)	-0.85 (-45.29–44.58)
Expected value				
Testing	1.30 (0.85–2.35)	1.25 (0.81–2.10)	1.08 (0.53–3.28)	1.49 (-18.78–19.67)
Traceability	0.78 (0.38–1.61)	0.74 (0.43–1.29)	0.50 (0.17–1.25)	0.04 (-2.91–4.07)
Animal health/welfare	1.02 (0.61–1.87)	1.01 (0.68–1.62)	1.00 (0.62–2.20)	0.36 (-8.12–8.39)
Ireland	4.45 (1.69–12.80)	4.14 (2.14–8.63)	2.85 (1.09–11.31)	3.04 (-35.85–39.26)
Great Britain	1.29 (-0.21–5.28)	1.01 (0.06–2.97)	0.27 (-0.47–2.63)	-0.06 (-13.54–14.03)

Note: The Krinsky and Robb (1986) simulation technique (using 100,000 draws) was employed to generate the empirical distributions of marginal willingness-to-pay. Correspondingly, the lower and upper limits of the 95% confidence interval are given by the 2,501$^{\text{th}}$ and 97,500$^{\text{th}}$ sorted estimates of marginal willingness-to-pay.

to right to left processing. However, it should be noted that it would also be possible to explore other orders (i.e., middle, left to right as well as middle, right to left). It would also be relatively straightforward to accommodate more than one processing ordering. For example, combining left to right and right to left would yield $944 \times 2 = 1,888$ satisficing rules. However, for the sake of brevity we do not report this analysis, but offer it as a suggestion for others who wish to further explore satisficing behavior in other stated choice experiments.

Appendix B: R code to accommodate satisficing

This appendix presents the code written in the R statistics program (R Core Team, 2016) to identify and accommodate satisficing behavior. It is intended to provide a resource for practitioners who are keen to explore and deal with satisficing behavior present in their own data. For demonstration purposes the code relates to a simplified example, but it can easily be adapted to suit other datasets.

The dataset is specified as having 1,000 respondents who each complete three choice tasks. The simulated stated choice experiment consists of three attributes (`x`, `y` and `z`), each with two levels (0 and 1) and three alternatives per choice task (the third alternative being 'buy neither', with the levels set to 0). For illustration purposes only, the attribute levels and choices are randomly generated. This is achieved using the syntax below.

```
nrespondents <- 1000
ntasks <- 3
x <- matrix(sample(0:1, ntasks * nrespondents * 2, replace = TRUE), ncol = 2)
y <- matrix(sample(0:1, ntasks * nrespondents * 2, replace = TRUE), ncol = 2)
z <- matrix(sample(0:1, ntasks * nrespondents * 2, replace = TRUE), ncol = 2)
choice <- sample(1:3, ntasks * nrespondents, replace = TRUE)
```

Assuming there are three possible satisficing rules per attribute (no rule applied; choose first alternative that has a level of 0; or, choose first alternative that has a level of 1), the total combinations of the satisficing rules can be obtained, defined as `S` in the syntax below.

```
S <- expand.grid(c(-999, 0:1), c(-999, 0:1), c(-999, 0:1))[-1, ]
```

The derivation of the satisficing probabilities in Eq. (6) begins with generating matrix **A** with elements to denote if the sequence of choices made by each respondent adheres to each satisficing condition. For this, object `A` is allocated to store the results during looping over the combinations of satisficing rules (based on left to right processing for demonstration purposes). Next, **B** is defined with diagonal entries equal to the column sums across rows of `A` diagonal and zero off-diagonal entries, which is denoted by `B` in the syntax below. Matrix **C** is obtained via matrix multiplication of the pseudoinverse inverse of `B` and `A`. This is coded as `C`, and is obtained with the use of the `ginv` function from package **MASS** (Venables and Ripley, 2002). Subsequently, `PI` and `omega` (which represent $\boldsymbol{\pi}$ and ω respectively) are obtained.

```
A <- matrix(0, ncol = dim(S)[1], nrow = nrespondents)
for (s in 1:dim(S)[1]) {
  if (S[s, 1] == -999) {
    alt1.obey.x <- alt2.obey.x <- optout.obey.x <- rep(1, ntasks * nrespondents)
  }
  if (S[s, 1] == 0) {
    alt1.obey.x <- ifelse(x[, 1] == 0, 1, 0)
    alt2.obey.x <- (1 - alt1.obey.x) * ifelse(x[, 2] == 0, 1, 0)
    optout.obey.x <- 1 - (alt1.obey.x + alt2.obey.x)
  }
  if (S[s, 1] == 1) {
    alt1.obey.x <- ifelse(x[, 1] == 1, 1, 0)
    alt2.obey.x <- (1 - alt1.obey.x) * ifelse(x[, 2] == 1, 1, 0)
    optout.obey.x <- 1 - (alt1.obey.x + alt2.obey.x)
  }
  if (S[s, 2] == -999) {
    alt1.obey.y <- alt2.obey.y <- optout.obey.y <- rep(1, ntasks * nrespondents)
  }
  if (S[s, 2] == 0) {
    alt1.obey.y <- ifelse(y[, 1] == 0, 1, 0)
    alt2.obey.y <- (1 - alt1.obey.y) * ifelse(y[, 2] == 0, 1, 0)
    optout.obey.y <- 1 - (alt1.obey.y + alt2.obey.y)
  }
  if (S[s, 2] == 1) {
    alt1.obey.y <- ifelse(y[, 1] == 1, 1, 0)
    alt2.obey.y <- (1 - alt1.obey.y) * ifelse(y[, 2] == 1, 1, 0)
    optout.obey.y <- 1 - (alt1.obey.y + alt2.obey.y)
  }
  if (S[s, 3] == -999) {
    alt1.obey.z <- alt2.obey.z <- optout.obey.z <- rep(1, ntasks * nrespondents)
  }
  if (S[s, 3] == 0) {
    alt1.obey.z <- ifelse(z[, 1] == 0, 1, 0)
    alt2.obey.z <- (1 - alt1.obey.z) * ifelse(z[, 2] == 0, 1, 0)
    optout.obey.z <- 1 - (alt1.obey.z + alt2.obey.z)
  }
  if (S[s, 3] == 1) {
    alt1.obey.z <- ifelse(z[, 1] == 1, 1, 0)
    alt2.obey.z <- (1 - alt1.obey.z) * ifelse(z[, 2] == 1, 1, 0)
    optout.obey.z <- 1 - (alt1.obey.z + alt2.obey.z)
  }
  obey.x <- alt1.obey.x * (choice == 1) + alt2.obey.x * (choice == 2) + optout.obey.x * (choice == 3)
  obey.y <- alt1.obey.y * (choice == 1) + alt2.obey.y * (choice == 2) + optout.obey.y * (choice == 3)
  obey.z <- alt1.obey.z * (choice == 1) + alt2.obey.z * (choice == 2) + optout.obey.z * (choice == 3)
  A[, s] <- apply(matrix(obey.x * obey.y * obey.z, nrow = ntasks), 2, prod)
}
B <- diag(apply(A, 1, sum))
require(MASS)
C <- ginv(B) %*% A
PI <- apply(C, 2, sum)/sum(apply(C, 2, sum))
omega <- sum(diag(B) != 0)/nrespondents
```

The log-likelihood functions for the multinomial logit model and the equivalent model that accommodates satisficing behavior are expressed in the functions `mnl.ll` and `mnl.sat.ll`, respectively. Both model functions have the argument `pars`, which is the vector of free parameters to maximize the log-likelihood. Both models assume a utility function that is linear in the parameters and, for illustration purposes only, there are no alternative specific constants. To demonstrate, the syntax below retrives the log-likelihood for both models where the marginal utilities for all attributes are zero.

```r
mnl.ll <- function(pars) {
  v1 <- pars %*% t(cbind(x[, 1], y[, 1], z[, 1]))
  v2 <- pars %*% t(cbind(x[, 2], y[, 2], z[, 2]))
  choice.prob <- (exp(v1) * (choice == 1) + exp(v2) * (choice == 2) + (choice == 3))/(exp(v1) + exp(v2) + 1)
  log(apply(matrix(choice.prob, nrow = ntasks), 2, prod))
}
mnl.sat.ll <- function(pars) {
  v1 <- pars %*% t(cbind(x[, 1], y[, 1], z[, 1]))
  v2 <- pars %*% t(cbind(x[, 2], y[, 2], z[, 2]))
  choice.prob <- (exp(v1) * (choice == 1) + exp(v2) * (choice == 2) + (choice == 3))/(exp(v1) + exp(v2) + 1)
  log((1 - omega) * apply(matrix(choice.prob, nrow = ntasks), 2, prod) + omega * (A %*% PI))
}
sum(mnl.ll(c(0, 0, 0)))
sum(mnl.sat.ll(c(0, 0, 0)))
```

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