Accommodating satisficing behavior in stated choice experiments

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Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, Massachusetts, July 31–August 2

May 25, 2016

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Accumulating evidence suggests that many respondents in stated choice experiments use simplifying strategies and heuristics. Such behavior is a deviation from random utility theory and can lead to biased estimates if not appropriately considered. This paper is a first attempt to systematically explore the use of the satisficing heuristic (Simon, 1955) in the context of a stated choice experiment. We consider 944 possible satisficing rules and allow respondents to revise the rules adopted throughout the choice sequence. While only a small proportion of respondents used the same satisficing rule across the entire sequence, allowing for changes in behavior at different stages reveals evidence that the use of the heuristic follows a learning and fatigue path. Furthermore, considering respondents satisficing leads to improved model fits and different marginal willingness-to-pay estimates.

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

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 of thumb to better manage 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., Hensher, 2006; Hensher et al., 2012; Hess et al., 2012; Swait and Adamowicz, 2001). 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 (Campbell et al., 2011; Hensher et al., 2005; Scarpa et al., 2012), use lexicographic decision rules (Hess et al., 2010, 2012; Scott, 2002), eliminate- or select alternatives based on the level of one or a few attributes (Erdem et al., 2014; Hess et al., 2012; Tversky, 1972) or minimize regret rather than maximize utility (Chorus et al., 2008; Thiene et al., 2012). However, only a handful of studies explore the issue of satisficing behavior (e.g., Grether and Wilde, 1984; Lindhjem and Navrud, 2011; Swait, 2001).

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 presented 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) instead of them continuing to search for the one that will maximize utility. This type of boundedly rational behavior is known as satisficing. Experimental evidence show that individuals make choices that are (partly) consistent with the satisficing heuristic (e.g., Caplin et al., 2011; Reutskaja et al., 2011; Stüttgen et al., 2012).

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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 (Papi, 2012; Tyson, 2008). Let us consider an individual facing a choice between different types of chicken in a food store. We denote the complete set of alternatives (i.e., different types of chicken) C. Furthermore, we assume that in this particular food store they only have three types of chicken $\{x, y, z\} \in C$. The alternatives are presented sequentially, from left to right, and we assume an individual will evaluate each in that order and select the one that meets the satisficing criterion. 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 $\{x, y, z\}$, $\{x, z, y\}$ and $\{z, x, y\}$ will all result in a utility maximizing choice. Any other combination of presenting the alternatives is likely to lead 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 a stated choice experiment a respondent often makes 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., Campbell et al., 2015; Czajkowski et al., 2014). 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.

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 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 chicken meat. 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. However, 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 follows a learning and fatigue pattern 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 satisficing heuristic, first proposed by Simon (1955), is concerned with individuals who are not maximizing utility but rather make choices based on an aspiration level leading to a satisfactory level of utility: in other words, choosing an alternative that is "good enough". Some experimental data 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 respondents use a stopping rule consistent with the satisficing heuristic.

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: (i) respondents are more likely to 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 (Carson et al., 1994; Downes-Le Guin et al., 2012; Krosnick, 1991).

For example, Holbrook et al. (2003) compare census data collected by phone with traditional face-to-face interviews and test the hypotheses of Krosnick (1991). The results show that phone respondents 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). The results show no difference between treatments in terms of engagement scores.

Within the stated preference literature, exploring satisficing has taken two distinct paths: one that follows the definitions and hypotheses set down by Krosnick (1991) and another that follows Simon (1955) more closely. For example, Lindhjem and Navrud (2011) compare an Internet 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. 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 her pre-determined cut-offs by imposing a utility cost for doing so.

3 Modeling approach

3.1 Background notation and RUM framework

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

$$U_{i_{nt}} = c_i + \beta' x_{i_{nt}} + \varepsilon_{i_{nt}}, \tag{1}$$

where c_i is an alternative specific constant, β' is a vector of parameters to be estimated, x_{i_n} is a 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 the probability of the sequence of choices $y_n = [i_{n1}, i_{n2}, \ldots, i_{nT}]$ can be estimated by the conventional multinomial logit model:

$$\Pr\left(y_n | x_{i_{nt}}, c, \beta\right) = \prod_{t=1}^{T_n} \frac{\exp\left(c_i + \beta' x_{i_{nt}}\right)}{\sum_{j=1}^{J} \exp\left(c_j + \beta' x_{j_{nt}}\right)}. \tag{2}$$

3.2 Addressing satisficing behavior

While the random utility maximization model described in Equation 1 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 increasing evidence show that this assumption may not hold. Instead, we might have to depart from this convenient assumption and allow for models that can capture boundedly rational behavior, and as such increase our model's capacity to accurately predict choice. We hypothesize that respondents satisfice when answering stated choice questionnaires, and instead of maximizing utility they make choices to reach a satisfactory level of utility. Specifically, when reading the choice card a respondent will choose the first alternative meeting a certain satisfactory level, thus completely disregarding all remaining options. Formally, a respondent chooses the first alternative that meets their satisficing requirements, meaning that the choice probability is given by:

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

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

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

When we think about satisficing, respondents' criteria are likely to be heterogeneous. That is, what is considered to be the minimum, acceptable or satisfactory level of utility or attribute level for one respondent may be different from that of another respondent. For example, while one respondent may choose the first alternative that is priced less than €10, another might focus more on a different attribute and choose the first alternative meeting a given level of it, while another will choose the first alternative that is priced in the range €10–20 *and* has a given level in another attribute. With the range of possible satisficing conditions denoted by S, the probability of respondent n's sequence of choices conditional on satisficing criterion s can be given by:

$$\Pr\left(y_n | x_{i_{nt}}, s\right) = \prod_{t=1}^{T_n} \Pr\left(i_{nt} | x_{i_{nt}}, s\right). \tag{4}$$

The overall choice probability can be obtained by allocating the full probability across all S satisficing rules and the random utility maximization model:

$$\Pr\left(y_n | x_{i_{nt}}, c, \beta, s\right) = \varpi^{c} \Pr\left(y_n | x_{i_{nt}}, c, \beta\right) + \varpi \sum_{s=1}^{S} \pi_s \Pr\left(y_n | x_{i_{nt}}, s\right), \tag{5}$$

where ϖ (derived below) is the unconditional probability that at least one of the S satisficing rules have been adopted, $\varpi^{c} = 1 - \varpi$ (i.e., the complement) is, therefore, the unconditional probability that the random utility maximization model is the appropriate framework, and $\varpi\pi_s$ (also derived below) is the unconditional probability associated with each satisficing rule. 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, unlike standard latent class models it is not required to estimate the class probabilities. These probabilities can be obtained by specifying a N-by-S matrix, A, where each element a_{ns} denotes a dummy variable, which takes the value of 1 if the entire sequence of T_n choices made by respondent n obeys satisficing condition s (which is equivalent to $\Pr\left(y_n|x_{i_{nt}},s\right)$):

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

Next, define B as a diagonal matrix:

$$B = \begin{bmatrix} b_1 & 0 & \dots & 0 \\ 0 & b_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & b_N \end{bmatrix}, \tag{6b}$$

where b_n is given by:

$$b_n = \begin{cases} \left(\sum_{s=1}^{S} a_{ns}\right)^{-1} & \text{if } \sum_{s=1}^{S} a_{ns} > 0; \\ 0 & \text{if otherwise.} \end{cases} \tag{6c}$$

Multiplication of matrices B and A yields C:

$$C = BA, \tag{6d}$$

the column means of which, provide the unconditional probability for each S satisficing rule (conditional on non random utility maximization decision-making):

$$\pi = N^{-1} \left[\sum_{n=1}^{N} c_{n1} \quad \sum_{n=1}^{N} c_{n2} \quad \dots \quad \sum_{n=1}^{N} c_{nS} \right] \tag{6e}$$

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

$$\varpi = \frac{\sum_{n=1}^{N} [b_n \neq 0]}{N}. \tag{7}$$

3.3 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, c_q and β_q, where $q = \{1,2,\dots,Q\}$. 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 c_q and β_q is denoted by $\varpi^c\pi_q$, subject to

$\sum_{q=1}^{Q} \pi_q = 1$, where π_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:

$$\Pr\left(y_n|x_{i_{nt}}, c_q, \beta_q, Q, s\right) = \varpi^{c} \sum_{q=1}^{Q} \pi_q \Pr\left(y_n|x_{i_{nt}}, c_q, \beta_q\right) + \varpi \sum_{s=1}^{S} \pi_s \Pr\left(y_n|x_{i_{nt}}, s\right). \tag{8}$$

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 case in 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 the willingness-to-pay for value-added services to chicken meat, specifically, two uncooked chicken breasts. Relevant attributes and the levels associated with this chicken product 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 chicken products that originate from either Ireland or Great Britain versus chicken products 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). Our prior parameter estimates were informed on the basis of initial estimations produced from the pilot study. The stated choice experiment consisted of a panel of twelve repeated choice tasks. To control for anchoring or focalism a number of 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.

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

When making their choices, respondents 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 chicken 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. The sample breakdown statistics for age, gender, income and residential location are comparable to the then current national population statistics.

5 Results

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 chicken product with the: (i) current standard; (ii) the enhanced standard; or, (iii) respondents do not use a rule for this attribute. For the region of origin attribute we consider five rules: either respondents choose the first chicken product originating (i) from 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 chicken product 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., $(3 \times 3 \times 3 \times 5 \times 7) - 1$)[1] possible satisficing decision-making rules, which we believe is sufficient to accommodate most (if not all) of the rules adopted by respondents.

In Table 2, we summarize the unconditional probabilities (Equation 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. This said, there is a sizable share (over 8 percent) who consistently choose the first[2] chicken product that originates from Ireland. This signals a strong sense of nationalism and preference for Irish chicken and the fact that respondents found it easier to identify with the regional label (e.g., as simple mark of freshness) compared to the other features. There is also a share (approximately 3.5 percent) who routinely, over the twelve choice tasks, choose the first chicken product 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, which makes 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) and the effects of learning and fatigue (Campbell et al., 2015) may change 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 in 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. Looking at 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 reasonable choice. 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 chicken 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 level.

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

[2] Note, in this analysis we assume respondents consider the alternatives from left to right.

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	2.135	5.298	7.347
Enhanced standard	3.499	4.568	4.373	11.190	9.884	8.416
Traceability						
Current standard	0.000	0.292	0.292	5.520	9.612	3.596
Enhanced standard	0.292	3.110	1.263	5.289	6.433	11.597
Animal health/welfare						
Current standard	0.000	0.292	0.292	4.165	7.852	2.235
Enhanced standard	0.583	0.875	0.875	8.371	6.367	9.015
Region of origin						
Ireland	8.163	10.787	9.913	18.129	14.500	13.605
Great Britain	0.292	0.292	0.292	1.277	1.380	2.430
Ireland/Great Britain	0.292	3.984	9.135	13.326	7.857	14.530
Outside Ireland/Great Britain	0.000	0.000	0.000	2.359	1.866	0.777
Price						
€2.50–3.00	0.875	0.875	1.749	4.859	1.833	2.391
€2.50–4.00	0.000	1.312	4.373	10.138	8.214	7.954
€2.50–5.00	0.000	0.777	0.437	6.115	2.996	8.368
€3.50–4.00	0.000	0.000	0.583	1.056	1.014	1.336
€3.50–5.00	0.000	0.146	0.729	6.807	0.816	6.269
€4.50–5.00	0.000	0.000	0.000	0.795	2.157	3.767
Satisficing and random utility maximization decision-making						
ϖ	13.994	25.948	34.111	75.802	67.347	84.257
ϖ^c	86.006	74.052	65.889	24.198	32.653	15.743

When we compare equivalent shares for the first four, middle four and last four choice tasks, these differences are even more apparent. In particular, 76, 67- and 84- percent of the choices in these sub-panels, respectively, comply with at least one satisficing rule. This result is consistent with the idea that respondents adjust their decision-making strategies as they go through a learning phase, followed by a phase where they are more proficient at making their choices and finally a fatigue phase. However, it is noted that our ability to identify satisfying 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. Comparing the relative magnitudes of these coefficients suggests that respondents place the highest value on chicken that has 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 chicken is predicted as having considerable lower importance. In accordance with prior expectations, the marginal utility for locally produced chicken is also found to be positive and significant—revealing that respondents are more likely to purchase chicken breasts originating in Ireland, relative to chicken 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 chicken product 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 chicken breasts.

Moving to the results obtained for Model 2, which accommodates satisficing, the second preference homogeneity model, we see that the signs and significance of the marginal utility parameters remain unchanged, which we note is not surprising given that the majority (86 percent) did not consistently adopt at least one 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

Table 3: Estimation results

(a) Preference homogeneity models

	Model 1		Model 2		Model 3		Model 4	
β_{Testing}	0.466***	(0.050)	0.402***	(0.047)	0.423***	(0.050)	0.346***	(0.077)
$\beta_{\text{Traceability}}$	0.262***	(0.050)	0.269***	(0.052)	0.278***	(0.054)	0.359***	(0.086)
$\beta_{\text{Animal health/welfare}}$	0.378***	(0.047)	0.400***	(0.050)	0.450***	(0.058)	0.434***	(0.088)
β_{Ireland}	1.049***	(0.088)	0.921***	(0.086)	0.894***	(0.092)	0.684***	(0.147)
$\beta_{\text{Great Britain}}$	0.166***	(0.062)	0.208***	(0.065)	0.207***	(0.070)	0.044	(0.097)
β_{Price}	-0.425***	(0.041)	-0.475***	(0.045)	-0.456***	(0.049)	-0.487***	(0.072)
$c_{j=1}$	0.018	(0.033)	0.018	(0.036)	-0.039	(0.040)	-0.202***	(0.064)
$c_{j=\text{none}}$	-1.885***	(0.209)	-2.298***	(0.230)	-2.241***	(0.250)	-2.399***	(0.379)
Log-likelihood	-3,553.479		-3,223.231		-3,259.894		-3,038.869	

Note: 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) Preference hetrogeneity models

	Model 5		Model 6		Model 7		Model 8	
Preference class 1								
β_{Testing}	0.468***	(0.055)	0.388***	(0.053)	0.420***	(0.055)	0.376***	(0.086)
$\beta_{\text{Traceability}}$	0.294***	(0.054)	0.313***	(0.062)	0.303***	(0.057)	0.443***	(0.101)
$\beta_{\text{Animal health/welfare}}$	0.425***	(0.053)	0.460***	(0.057)	0.490***	(0.063)	0.523***	(0.109)
β_{Ireland}	0.699***	(0.083)	0.795***	(0.091)	0.822***	(0.098)	0.680***	(0.153)
$\beta_{\text{Great Britain}}$	0.204***	(0.067)	0.232***	(0.073)	0.250***	(0.075)	0.055	(0.104)
β_{Price}	-0.479***	(0.050)	-0.496***	(0.054)	-0.491***	(0.056)	-0.575***	(0.089)
$c_{j=1}$	0.030	(0.035)	0.021	(0.039)	-0.046	(0.041)	-0.199***	(0.066)
$c_{j=\text{none}}$	-3.482***	(0.232)	-4.101***	(0.594)	-3.947***	(0.256)	-4.275***	(0.472)
$\pi_{q=1}$	0.806***	(0.050)	0.834***	(0.067)	0.865***	(0.057)	0.881***	(0.083)
Preference class 2								
β_{Testing}	0.868***	(0.234)	0.885***	(0.218)	1.224***	(0.244)	1.659**	(0.764)
$\beta_{\text{Traceability}}$	0.435**	(0.196)	-0.074	(0.400)	0.139	(0.222)	1.001**	(0.605)
$\beta_{\text{Animal health/welfare}}$	0.446**	(0.205)	0.049	(0.217)	0.447**	(0.215)	0.494	(1.126)
β_{Ireland}	5.197***	(0.541)	2.409*	(1.544)	2.380***	(0.318)	3.603	(4.081)
$\beta_{\text{Great Britain}}$	1.290**	(0.574)	0.460	(1.408)	-0.036	(0.432)	1.847	(2.640)
β_{Price}	-0.406***	(0.109)	-0.600***	(0.208)	-0.628***	(0.135)	-0.416*	(0.292)
$c_{j=1}$	-0.008	(0.130)	0.002	(0.132)	0.174	(0.234)	-0.166	(0.654)
$c_{j=\text{none}}$	3.351***	(0.739)	0.330	(2.557)	1.138**	(0.649)	5.160*	(3.235)
$\pi_{q=2}$	0.194***	(0.026)	0.166***	(0.041)	0.135***	(0.021)	0.119***	(0.031)
Log-likelihood	-3,014.305		-2,826.018		-2,962.901		-2,856.733	

Note: 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.

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, on the basis of the log-likelihood there appears to be little support for this, since Model 2 has 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 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. Interestingly, this model is associated with a better fit compared to the other models that assume preference homogeneity.

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 chicken originating in 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 chicken. While not surprising, it does signal 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, which reinforces the notion that the first option meeting the satisficing criterion is chosen and not the first alternative encountered.

As noted earlier, the assumption of preference homogeneity is unlikely to hold and we allow for heterogeneity using a discrete distribution to describe preferences. In Table 3(b) we show the result of this estimation using two latent classes (i.e., two support points for the distribution of preferences). 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—represent 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 chicken (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 chicken 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 prefer to go without chicken. Both classes have in common strong preferences for chicken originating in 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 shorter sub-panels of even more 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 for Irish chicken, compared to €1.11 for chicken that has undergone enhanced food testing, €0.90 for chicken produced under enhanced animal health/welfare standards, €0.62 for fully traceable chicken and €0.40 for chicken 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. Most noteworthy is the downward shift in value associated with chicken originating from Ireland as well as chicken subject to enhanced testing. Referring back to Table 2, these were the attributes levels most 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 manner in which 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

Table 4: Marginal willingness-to-pay (€ per chicken product) (95% confidence intervals in parentheses)

(a) Preference homogeneity 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)	0.73 (0.39–1.14)
Traceability	0.62 (0.38–0.88)	0.57 (0.35–0.81)	0.62 (0.38–0.88)	0.74 (0.42–1.10)
Animal health/welfare	0.90 (0.67–1.15)	0.85 (0.64–1.08)	1.00 (0.74–1.30)	0.90 (0.56–1.31)
Ireland	2.50 (1.91–3.23)	1.96 (1.50–2.51)	1.99 (1.47–2.63)	1.44 (0.77–2.30)
Great Britain	0.40 (0.10–0.74)	0.44 (0.17–0.76)	0.46 (0.15–0.81)	0.09 (-0.31–0.52)

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 2,500th and 97,500th sorted estimates of marginal willingness-to-pay.

(b) Preference hetrogeneity models

	Model 5	Model 6	Model 7	Model 8
Preference class 1				
Testing	0.99 (0.73–1.30)	0.79 (0.57–1.05)	0.86 (0.62–1.16)	0.67 (0.35–1.07)
Traceability	0.62 (0.39–0.87)	0.64 (0.39–0.91)	0.62 (0.39–0.88)	0.78 (0.46–1.13)
Animal health/welfare	0.89 (0.67–1.15)	0.94 (0.71–1.20)	1.01 (0.75–1.31)	0.92 (0.58–1.30)
Ireland	1.47 (1.06–1.97)	1.62 (1.18–2.18)	1.70 (1.22–2.30)	1.21 (0.63–1.97)
Great Britain	0.43 (0.14–0.76)	0.48 (0.18–0.82)	0.52 (0.20–0.89)	0.10 (-0.26–0.49)
Preference class 2				
Testing	2.37 (0.91–5.04)	1.84 (0.51–5.64)	2.02 (1.19–3.29)	4.44 (-14.44–23.25)
Traceability	1.18 (0.13–2.85)	0.06 (-1.11–2.71)	0.24 (-0.48–1.10)	2.26 (-6.03–11.70)
Animal health/welfare	1.26 (0.09–3.34)	0.16 (-0.59–1.54)	0.75 (0.04–1.70)	0.14 (-16.52–18.95)
Ireland	14.32 (7.43–29.16)	5.37 (-0.80–22.38)	4.03 (2.28–7.14)	15.75 (-85.80–115.55)
Great Britain	3.48 (0.40–8.13)	1.50 (-2.99–12.30)	0.00 (-1.34–1.64)	8.41 (-55.40–72.14)
Expected value				
Testing	1.25 (0.89–1.80)	0.93 (0.63–1.43)	1.02 (0.74–1.37)	1.22 (-1.07–3.62)
Traceability	0.72 (0.45–1.08)	0.52 (0.20–0.86)	0.57 (0.34–0.82)	1.02 (0.01–2.22)
Animal health/welfare	0.96 (0.68–1.37)	0.80 (0.53–1.09)	0.97 (0.73–1.26)	0.80 (-1.07–3.32)
Ireland	3.94 (2.31–7.13)	2.07 (0.95–4.02)	2.02 (1.46–2.73)	4.19 (-8.64–14.22)
Great Britain	1.03 (0.38–2.08)	0.53 (-0.39–1.73)	0.45 (0.11–0.83)	1.85 (-6.15–8.28)

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.

obtained for each latent class shows a clear difference. In particular, we draw attention to the very high (and unrealistic) value of €14.32 respondents in the second (smaller) class are found to place on Irish chicken under Model 5. Crucially, as we move to Model 6, the equivalent value of €5.37 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 1.2–2.0 times higher relative to the more reliable model that also addresses satisficing.

6 Conclusions

In this paper, we explored respondent's use of satisficing choice behavior in the context of a stated choice experiment that we conducted in the Republic of Ireland, which aimed at eliciting preferences for value-added services to uncooked chicken breasts. 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 specify in our model.

First, we find that considering respondents satisficing leads to improved model fits relative to the models failing to do so. We find that only a small proportion of respondents adopt a satisficing rule across the entire sequence of choices. A majority of respondents adopting a satisficing heuristic chose the first alternative with chicken originating in 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 satisficing heuristic is consistent with the notion of learning and fatigue. Although we do note 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.

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, to our knowledge this data has not been used to systematically explore satisficing. Extending research in this direction could prove fruitful. 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.

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