

# Choosing 'buy none' in food choice analysis: the role of utility balance\*

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## Abstract

Stated choice analysis is now a widely used and accepted methodology for exploring food choice. In stated choice experiments respondents are asked to make a choice between two or more alternatives, one of which typically takes the form of a 'buy none' option. It is widely recognised that respondents often perceive this option differently from the other alternatives and various reasons for this have been offered. Nevertheless, the role that utility balance among the experimentally designed options plays on the propensity of respondent's choosing 'buy none' has largely been overlooked. Using a non-linear representation of utility we show that the 'buy none' choices are sensitive to utility balance. We further show how accommodating this provides an additional insight into choice behaviour and has a bearing on welfare calculations.

**Keywords:** discrete choice experiments, utility balance, status-quo bias, food choice

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## 1 Introduction

Since its introduction there has been a growing number of studies using the stated choice experiment methodology. Discrete choice experiments are appealing as value derivation techniques because they are consistent with the Lancasterian microeconomic approach (Lancaster, 1966), whereby individuals derive utility from the different characteristics, or attributes, that a good possesses, rather than directly from the good *per se*. Accordingly, a change in the level of an attribute describing a given alternative may cause the respondent to favour that alternative over another that is perceived as providing an inferior combination of attributes. In discrete choice experiments, respondents are asked to select their preferred alternative from a given set (the choice set), and are typically asked to perform a sequence of such choices giving rise to a panel of discrete choices. Experimental design theory is used to construct the alternatives, which are defined in terms of their attributes and the levels these attributes could take. This type of analysis has been widely used to derive welfare estimates for ecological and environmental goods.

Typically the choice task respondents are faced with includes an option to 'buy none', usually referred to as the status-quo (SQ) alternative. The inclusion of such an alternative provides realism and ensures that the resulting welfare estimates are theoretically consistent with welfare economics. However, it is widely remarked that respondents can perceive this alternative differently from the other alternatives. While a number of reasons for this have been suggested (e.g., see Kontoleon and Yabe, 2003; Samuelson and Zeckhauser, 1988; Scarpa et al., 2005, 2007, for an overview), the role that the degree of utility balance between the non-SQ alternatives plays has largely been overlooked (despite the fact that it has been shown by Hauser and Toubia (2005) to effect the partworth estimates). This paper seeks to address this gap in the literature. The argument here is that, as the degree of utility balance between the non-SQ alternatives increases, making a choice between them becomes increasing burdensome and that this may lead to a higher propensity of respondents choosing the SQ option.

To accommodate this issue, in this paper we use a non-linear representation of utility to isolate the impact of utility balance on respondent's SQ choices. Moreover, we opt for a specification that accommodates the random taste variation. The rationale for this stems from the recognition that the degree of utility balance is respondent-specific (i.e., the actual probability of choosing an alternative depends on their preferences). We further acknowledge that this phenomenon may not be associated with all respondents and, thus, our modelling approach is aimed at retrieving probabilistic estimates of this type of behaviour. Results, based on an empirical dataset exploring the demand for value-added services to food, reveal that a share of respondent's decision to choose the 'buy none' option was influenced by the degree of utility balance among the none SQ options. Results further show that accounting for this leads to gains in model fit and that failing to account for it has implications for market

predictions.

The remainder of the paper is structured as follows: [Section 2](#) outlines our empirical case-study; [Section 3](#) describes our modelling approach; [Section 4](#) presents the results from the analysis; and, [Section 5](#) concludes.

## 2 Case-study: demand for assured, safe and traceable food

To identify the relevant food safety attributes and levels, the study design was informed by expert opinion from food scientists involved in developing methods to verify the safety and authenticity of food. After discussions, three safety attributes were identified. These included food testing standards, traceability standards and health and welfare standards of the food-producing animals. These attributes were presented at two levels in the choice experiment—a current and enhanced standard. For the 'food testing' attribute, the enhanced standard represented the use of additional testing to ensure safer food. For the 'traceability' attribute, the enhanced standard consisted of the use of technology to verify the exact origins of the meat so that labelling fraud could not occur. For the 'animal health and 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 sourced within the British Isles *versus* chicken products that came from outside this area. A final attribute was included which depicted the price levels of the chicken products, which was presented for a tray of two chicken breasts. Although expert opinion ensured the information on the levels was correct and relevant to the scientific developments in these areas, a series of focus group discussions were also held to determine whether the levels were understandable and relevant to the general public. This ensured that consumers could understand and differentiate between the levels as well as the choice alternatives. It also gave an indication of the number of choice sets to present in the choice experiment.

After the feedback from scientific experts and focus groups, a Bayesian efficient experimental design was generated, based on the minimisation of the  $D_b$ -error criterion (for a general overview of efficient experimental design literature, see e.g., [Scarpa and Rose, 2008](#), and references cited therein). The design comprised of a panel of twelve choice tasks. For each task, respondents were asked to choose between two experimentally designed alternatives and a 'buy none' option. When making their choices, respondents were asked to consider only the information presented in the choice task and to treat each task separately. Respondents were also reminded that if they thought the alternatives were too expensive, or if they did not normally buy chicken, they could simply choose the 'buy none' option. In total, this paper uses responses collected via an on-line survey from 622 respondents residing in Great Britain, resulting in 4,976 observations for model estimation.

### 3 Modelling approach

Starting with the conventional specification of utility, where respondents are indexed by  $n$ , chosen alternatives by  $i$ , available alternatives by  $J$ , choice occasions by  $t$ , the attributes are represented by  $x$  and  $\delta$  is a dummy variable equalling 1 when the alternative is the SQ, we have:

$$U_{nit} = \beta x_{nit} + \delta C + \varepsilon_{nit}, \quad (1)$$

where  $\beta$  are parameters to be estimated for the attributes,  $C$  represents a constant for the SQ alternative, and  $\varepsilon$  is an *iid* type I extreme value (EV1) distributed error term, with constant variance  $\pi^2/6$ . Given these assumptions, the probability of the sequence of choices made by individual  $n$  can be represented by the multinomial logit (MNL) model:

$$\Pr(y_n|x_n) = \prod_{t=1}^{T_n} \frac{\exp(\beta x_{nit} + \delta C)}{\sum_{j=1}^J \exp(\beta x_{njt} + \delta C)}, \quad (2)$$

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

Given our focus on exploring SQ effects, as outlined in [Scarpa et al. \(2005\)](#), an error component specification is a useful starting point, since it facilitates the substitutions patterns between the non-SQ alternatives. This can be achieved using the following specification:

$$\Pr(y_n|\eta, x_n) = \int_{\eta} \prod_{t=1}^{T_n} \frac{\exp(\beta x_{nit} + \delta C + (1 - \delta)\eta)}{\sum_{j=1}^J \exp(\beta x_{njt} + \delta C + (1 - \delta)\eta)} f(\eta) d(\eta), \quad (3)$$

where  $\eta$  is the error component and is specified as  $\eta \sim \mathcal{N}(0, \sigma^2)$  to capture the choice situation invariant variation that is unobserved and not accounted for by the other model components. In addition to this, there can also be heterogeneity in the preferences respondents hold for the attributes. For this reason, there has been a growth in models which attempt to uncover and explain the heterogeneity across respondents. Indeed, in the food choice literature it is increasingly now common practice to use models, such as mixed logit specifications, to handle preference heterogeneity (e.g. [Balcombe et al., 2009](#); [Rigby and Burton, 2006](#)), by treating the coefficients as random. Moreover, as discussed in [McFadden and Train \(2000\)](#), these mixed logit models provide a flexible and computationally practical econometric method, which with adequate data quality, may in principle be used to approximate any discrete choice model derived from random utility maximization.

With  $\theta$  representing the combined vector of  $\beta$  and  $\eta$ , the unconditional choice

probability is obtained by integrating the logit probability over all possible values of  $\theta$ :

$$\Pr(y_n|\theta, x_n) = \int_{\theta} \prod_{t=1}^{T_n} \frac{\exp(\beta x_{nit} + \delta C + (1 - \delta)\eta)}{\sum_{j=1}^J \exp(\beta x_{njt} + \delta C + (1 - \delta)\eta)} f(\theta) d(\theta), \quad (4)$$

where we assume  $\beta \sim \mathcal{N}(\mu, \sigma^2)$  for all attributes except for cost where we opt for a Triangular distribution specified as follows:  $\beta_{\$} \sim \mathcal{T}(\mu_{\$} - \sigma_{\$}, \mu_{\$}, \mu_{\$} + \sigma_{\$})$  and where the constraint  $\sigma_{\$} \leq |\mu_{\$}|$  is placed to ensure the distribution is bounded within a given orthant, which is advantageous given the theoretical inconsistency of observing a positive value for the cost coefficient.

Thus far we have assumed that the SQ choices are not influenced by the degree of overlap between the non-SQ alternatives. In this paper our focus is on highlighting the role that utility balance plays on respondent's tendency of choosing the SQ alternative. Utility balance, which is typically an issue discussed in relation to experimental design (e.g., [Scarpa and Rose, 2008](#); [Huber and Zwerina, 1996](#)), is a measure of the similarity in choice probabilities of two or more alternatives. The argument here is that, as the degree of utility balance between the non-SQ alternatives increases, making a choice between them becomes increasingly burdensome and that this may lead to a higher propensity for respondents to choose for the SQ option.

The measure of utility balance (denoted by  $\mathcal{B}$ ) between the  $G$  non-SQ alternatives for a given choice task can be calculated as follows:

$$\mathcal{B} = \frac{\prod_{g=1}^G \Pr(y = g)}{\left(\frac{1}{G}\right)^G}. \quad (5)$$

The value of  $\mathcal{B}$  ranges between 0 and 1, with the value representing how balanced the probabilities are over the alternatives within the choice task. As  $\mathcal{B} \rightarrow 0$  it is an indication that the choice task contains a completely dominant alternative (in which case choosing the preferred alternative does not require substantial cognitive effort), whereas the probabilities across all alternatives become increasingly balanced as  $\mathcal{B} \rightarrow 1$  (thus, requiring the respondent to invest considerable cognitive effort to ensure they maximise their expected utility).

In this paper we achieve this by re-parameterising the variable  $C$  in the above specifications as follows:

$$C = c + \varphi\omega\mathcal{B}, \quad (6)$$

where the  $c$  now captures the influence the SQ constant, *ceteris paribus*, and  $\omega$  explains the influence of utility balance among the non-SQ options on the SQ choice. However, we recognise that it may not be the case that all respondents will exhibit this type of behaviour. We, therefore, introduce a further parameter ( $\varphi$ ) into Equation 6, which we specify as a discrete variable as follows:

$$\varphi = \begin{cases} 1 & \text{if respondent's SQ choices are influenced by utility balance;} \\ 0 & \text{if otherwise.} \end{cases} \quad (7)$$

Associating the probabilities of  $\varphi_1$  and  $\varphi_0$  with  $\pi_{\varphi_1}$  and  $\pi_{\varphi_0}$  respectively provides an intuitive meaning:  $\pi_{\varphi_1}$  gives an indication of the proportion of respondents whose SQ choices were influenced by the degree of utility balance among the non-SQ alternatives, whereas  $\pi_{\varphi_0}$  relates to the share of respondents who are not influenced by utility balance. Based on this, the overall choice probability is given by:

$$\Pr(y_n|\theta, x_n) = \sum_{\forall S} \pi_s \int_{\theta} \prod_{t=1}^{T_n} \frac{\exp(\beta x_{nit} + \delta(c + \varphi\omega\mathcal{B}) + (1 - \delta)\eta)}{\sum_{j=1}^J \exp(\beta x_{njt} + \delta(c + \varphi\omega\mathcal{B}) + (1 - \delta)\eta)} f(\theta) d(\theta), \quad (8)$$

where  $S = \{0, 1\}$  representing the two possible values of  $\varphi$  (i.e., with  $s_0$  relating to the case where respondent's SQ choices are not influenced by utility balance, we would have that  $\pi_{s_0} = \pi_{\varphi_0}$  and  $\varphi = 0$ , whereas with  $s_1$  relating to the case where respondent's SQ choices are influenced by utility balance, we would have that  $\pi_{s_1} = \pi_{\varphi_1}$  and  $\varphi = 1$ ).

## 4 Results

### 4.1 Estimation results

Table 1 presents results from four models, with marginal utilities for the food and price attributes and with different specifications capturing the SQ effects, described as follows<sup>1</sup>:

**MNL model** A standard MNL model (as outlined in Equation 2).

**MXL model** A error component and random parameters models (as specified in Equation 4).

**MNL-UB model** Similar to the MNL model, but where  $C$  is re-parametrised in accordance with Equation 6.

<sup>1</sup>Since the choice probabilities in specifications MXL and MXL-UB cannot be calculated exactly (because the integrals do not have a closed form), we estimate them by simulating the log-likelihood with 150 quasi-random draws via Halton sampling.

**MXL-UB model** Similar to the MXL model, but where  $C$  is re-parametrised in accordance with Equation 6 (i.e., the overall choice probability as set out in Equation 8).

Looking firstly at the MNL model results reveals, as expected, that the coefficients retrieved for the three food safety attributes are all estimated as having a positive, and significant, sign—implying that respondents, *ceteris paribus*, have a preference for the ‘value-added’ services to food. Comparing the magnitudes of these parameter estimates suggests that respondents place the highest value on food that has undergone enhanced testing to ensure food safety and that the food was produced free of harmful drugs and diseases, whereas the ability to fully trace the food played a lesser role on respondent’s choices. In line with expectations, the coefficient for the lo-

Table 1: Estimation results

	MNL		MXL		MNL-UB <sup>a</sup>		MXL-UB <sup>a</sup>	
	est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.
$\beta_{\text{Testing}}$	0.766	18.98	-	-	0.729	18.52	-	-
$\mu_{\text{Testing}}$	-	-	1.127	16.35	-	-	1.157	15.47
$\sigma_{\text{Testing}}$	-	-	0.982	13.59	-	-	1.024	13.33
$\beta_{\text{Traceable}}$	0.445	11.69	-	-	0.351	9.94	-	-
$\mu_{\text{Traceable}}$	-	-	0.641	13.38	-	-	0.625	12.73
$\sigma_{\text{Traceable}}$	-	-	0.063	0.37	-	-	0.114	0.50
$\beta_{\text{Welfare}}$	0.714	17.39	-	-	0.624	16.00	-	-
$\mu_{\text{Welfare}}$	-	-	1.037	15.60	-	-	1.017	14.65
$\sigma_{\text{Welfare}}$	-	-	0.927	12.50	-	-	0.928	12.64
$\beta_{\text{Local}}$	0.189	4.26	-	-	0.173	4.40	-	-
$\mu_{\text{Local}}$	-	-	0.340	5.31	-	-	0.323	5.07
$\sigma_{\text{Local}}$	-	-	0.652	6.66	-	-	0.656	6.12
$\beta_{\text{Price}}$	-0.668	24.70	-	-	-0.601	21.85	-	-
$\mu_{\text{Price}}$	-	-	-1.026	22.08	-	-	-1.010	19.91
$\sigma_{\text{Price}}$	-	-	1.026	21.52	-	-	1.010	19.91
$C$	-2.317	24.83	-5.334	17.56	-	-	-	-
$\sigma_{\eta}$	-	-	3.622	14.73	-	-	4.508	12.03
$c$	-	-	-	-	-2.831	-29.362	-6.495	13.35
$\omega$	-	-	-	-	1.573	24.379	2.684	10.93
$\pi_{\varphi_1}$	-	-	-	-	0.083	6.486	0.092	2.96
$\mathcal{L}(\hat{\beta})$	-4,168.53		-3,515.10		-3,918.24		-3,511.86	
$K$	6		12		8		14	
$\bar{\rho}^2$	0.236		0.355		0.282		0.355	
AIC/ $N$	1.678		1.418		1.578		1.417	
BIC/ $N$	1.686		1.433		1.589		1.435	

<sup>a</sup> Since  $\pi_{\varphi_1} + \pi_{\varphi_0} = 1$ , for the sake of brevity we only report  $\pi_{\varphi_1}$ .

cally produced attribute is found to be also positive, and significant—revealing that, other things being equal, respondents prefer food that is produced in the British Isles compared to food produced elsewhere. In line with *a-priori* expectations the coefficients obtained for the price attribute and SQ constant are both estimated as having negative, and significant, signs—implying that, all else held constant, respondents (i) prefer food that is less expensive, and (ii) dislike the situation of not having the food.

The MXL model is aimed at addressing the substitution patterns between the non-SQ alternatives and concurrently the random taste variation across the respondents for the choice experiment attributes. We note that, as one would expect following the results under the MNL model, the means of random parameters are all found to be significant and have the same sign as those uncovered under the MNL specification. We further note that the significant standard deviations for the food attributes (with the exception of the traceability attribute) leads to the rejection of the null hypothesis of preference homogeneity among the respondents. The significant spread parameter for the price attribute implies that respondents also differed in their marginal utility of money (dis-utility for the price attribute). We note that, once again, the SQ constant is negative and significant. The parameter capturing the substitution patterns among the non-SQ effects is significant, suggesting that utility from the experimentally designed alternatives are more correlated among themselves than with the utility associated with the SQ. We observe that allowing for this more flexible specification leads to an improvement in model fit compared to the MNL model. We also note an improvement of over 650 log-likelihood units at the expense of fitting six additional parameters, which contributes to a likelihood ratio statistic of 1,306.86 against the  $\chi^2$  critical value of 12.59 ( $\chi^2_{6,0.05}$ ).

Under both the MNL and MXL model specifications we observe a relatively high constant for the SQ alternative. In this paper we aim at disentangling the influence that utility balance may play on this coefficient. We, therefore, replicate the MNL and MXL models, but attempt to isolate the impact that utility balance has on the SQ choices and gauge the proportion of the sample who exhibit this type of behaviour.

Inspection of the MNL-UB model results reveals that the values of  $\omega$  and  $\pi_{\varphi_1}$  are both significant, which is an important finding. The fact that  $\omega$  is positive implies that situations where utilities associated with the non-SQ alternatives are relatively comparable, the tendency for choosing the SQ alternative is higher and, thereby, respondents choices are influenced by the level of utility balance among the non-SQ options. However, as identified by the value of  $\pi_{\varphi_1}$  we note that this type of behaviour is not exhibited by all respondents, but, rather, only by a relative minority of respondents (just less than 10 percent). While the remaining SQ constant is again found to be negative, and significant, we remark that, for the subset of respondents whose SQ choices are influenced by utility balance, the SQ effect is found to almost disappear when the non-SQ alternatives are relatively balanced. While inferences relating to the other coefficients remain relatively unchanged from the MNL model, we note that this model is associated with an improved model fit. Indeed, the improvement

of just over 250 log-likelihood units at the expense of two additional parameters provides a likelihood ratio test statistic of 500.59 against the  $\chi^2$  critical value of 5.99 ( $\chi^2_{2,0.05}$ ).

In our final model we recognise the role of preference heterogeneity as well as the fact that the degree of utility balance is respondent-specific (i.e., the actual probability of choosing an alternative depends on their preferences). For this reason, we use the same specification as used in the MXL model, but allow for the influence of utility balance. An inspection of the value uncovered for utility balance effect coefficient from this MXL-UB model reveals that is positive, and significant, thus confirming the conclusions reached from the MNL-UB model. However, once again, we find that this behaviour applies to only a small subset (less than 10 percent) of respondents. The SQ constant and error component parameters are both significant, which is in accordance with the previous models. We note that inferences concerning the remaining coefficients are in line with those obtained under the MXL model. We further remark that the MXL-UB model obtains the best model fit. Moreover, with likelihood ratio test statistics of 6.47 and 812.75 against  $\chi^2$  critical values of 5.99 ( $\chi^2_{2,0.05}$ ) and 12.59 ( $\chi^2_{6,0.05}$ ) for the MXL-UB model *versus* the MXL and MNL-UB models respectively, we can reject the null hypothesis that the more flexible specification does not lead to a better model fit. This improvement in fit is supported by the  $\bar{\rho}^2$ , AIC and BIC statistics, even after penalising for the additional parameters.

#### 4.2 Willingness to pay and demand for assured, safe and traceable food

Using the parameters reported in [Table 1](#), we can derive the marginal willingness to pay (WTP) for each of the food attributes. Results from these calculations reveal remarkable stability in the estimates. Irrespective of the model specification, the highest computed marginal WTP estimates are associated with the testing and welfare attributes (approximately £1.15 and £1.05 respectively for two chicken breasts), with the lowest values relating to locally produced attribute (approximately £0.30 for two chicken breasts) and with the traceability attribute ranking in-between (approximately £0.70 for two chicken breasts)<sup>2</sup>.

An alternative way of teasing out the effect of not recognising the role of utility balance in some respondent's choices is to explore the impact on market share predictions. For this analysis we consider a hypothetical sample of 100,000 consumers and that their choice of chicken breasts are restricted to the following:

**Current standard** Two standard food safety chicken breasts (standard food testing, traceability and welfare), that are produced outside of the British Isles and are priced £2.00.

<sup>2</sup>We note that in the case of the MXL and MXL-UB models, these marginal WTP estimates relate only to the mean of the distribution.

Table 2: Market share analysis

	MNL	MXL <sup>a</sup>	MNL-UB	MXL-UB <sup>a</sup>
No utility balance effect				
Market size (consumers)	100,000	100,000	91,745	90,772
Standard chicken market share (%)	42.106	40.881	46.052	42.094
Enhanced chicken market share (%)	42.106	42.854	44.916	43.887
Buy neither market share (%)	15.787	16.265	9.032	14.019
Total revenue (£)	301,679	303,088	297,329	282,158
Utility balance effect				
Market size (consumers)	-	-	8,255	9,228
Standard chicken market share (%)	-	-	34.24	37.279
Enhanced chicken market share (%)	-	-	33.39	39.858
Buy neither market share (%)	-	-	32.37	22.864
Total revenue (£)	-	-	19,890	25,882
Total				
Market size (consumers)	100,000	100,000	100,000	100,000
Standard chicken market share (%)	42.106	40.881	45.077	41.649
Enhanced chicken market share (%)	42.106	42.854	43.965	43.515
Buy neither market share (%)	15.787	16.265	10.958	14.836
Total revenue (£)	301,679	303,088	317,219	308,040

<sup>a</sup> Based on the means of the unconditional distributions (generated from 100,000 random draws)

**Enhanced standard** Two enhanced food safety chicken breasts (enhanced food testing, traceability and welfare), that are produced within the British Isles and are priced £5.16<sup>3</sup>.

There is also the further option whereby consumers can decide not to buy any of the chicken breasts. Based on this, and on the parameters estimated under each of the models, we predict the proportion of the hypothetical sample of consumers who would buy each type of chicken breasts and who would purchase neither. Results from this investigation are reported in Table 2. Based on the MNL model parameter estimates, the predicted market share for each type of chicken is just over 42 percent, with the remaining (almost 16 percent of the consumers) predicted to buy neither type of chicken. Based on this, the total revenue equates to just over £300,000. Despite the more flexible specification used in the MXL model, the predicted market shares and total revenue are quite comparable to those reached under the MNL model.

Turning to the MNL-UB and MXL-UB models, where the influence that utility balance has on the tendency for choosing the SQ is accommodated, we report separate predictions for the larger subset of consumers who did not exhibit this type of behaviour and the smaller subset of who did. Based on the predictions generated from

<sup>3</sup>The price of £5.16 has been derived as it represents the value at which there is utility balance between the two scenarios using the MNL model parameters

these models, we find, irrespective of whether or not their decisions to buy neither were influenced by the degree of utility balance among the two types of chicken, the proportions predicted for the standard and enhanced chicken are analogous, as one would expect. However, the proportions of respondents predicted to buy neither type of chicken differ considerably between the two subsets, to the extent that predictions of non-purchasing may be upwardly biased in the naïve MNL and MXL model specifications. As can be seen, this has implications for the predictions of total revenue generated from this hypothetical sample of consumers (a increase of over 5 percent when comparing the MNL-UB model predictions against those computed under the MNL model). Examining the market share predictions for consumers whose choices are influenced by utility balance, clearly shows their increased tendency not to buy any of the chicken breasts, possibly reflecting their reluctance to invest the necessary cognitive effort.

## 5 Conclusions

Results based on a stated choice experiment exploring the demand for value-added services to food among consumers in the Great Britain, provide confirmation that a share of respondent's decision to choose the 'buy none' option was influenced by the degree of utility balance among the none SQ options. This suggests that some of these SQ choices may actually reflect a simplifying heuristic, reflecting the reluctance of some respondents to invest the necessary cognitive effort to decide between two relatively comparable alternatives.

While the majority of the sample are still probabilistically identified as not exhibiting this type of behaviour, our approach nevertheless provides a framework for isolating the impact of utility balance on SQ choices. Our analysis provides evidence for the need to disentangle the role of utility balance and status-quo effects. Results further show that accounting for this leads to gains in model fit and that failing to account for it has implications for market predictions. Crucially, our analysis highlights the fact that predictions of non-purchasing may be upwardly biased unless the role of utility balance is accounted for, which we ultimately show has implications for revenue predictions (possibly differences of over 5 percent).

Results in this paper highlight the need to fully explore reasons for SQ choices. While our analysis shows this from the estimation point of view, knowledge of the fact SQ choices may also be influenced by the degree of utility balance among the non-SQ alternatives should also help at the experimental design stage. Indeed, implementing this type of analysis to data collected during piloting should ensure that the design used in the main survey is appropriate. Doing so should help avoid the situation of upwardly biasing the proportion of SQ choices as a form of heuristic. Our findings also provide compelling evidence for further research in this area. Future studies should incorporate procedures for identifying and dealing with the role of

utility balance on respondent's choices so that the sensitivity on model performance and welfare estimates can be further evaluated.

## References

- Balcombe, K., Chalak, A. and Fraser, I. (2009). Model selection for the mixed logit with bayesian estimation, *Journal of Environmental Economics and Management* **57**(2): 226–237.
- Hauser, J. R. and Toubia, O. (2005). The impact of utility balance and endogeneity in conjoint analysis, *Marketing Science* **24**: 498–507.
- Huber, J. and Zwerina, K. (1996). The importance of utility balance in efficient choice designs, *Journal of Marketing Research* **33**(3): 307–317.
- Kontoleon, A. and Yabe, M. (2003). Assessing the impacts of alternative 'opt-out' formats in choice experiment studies: consumer preferences for genetically modified content and production information in food, *Journal of Agricultural Policy and Resources* **5**: 1–43.
- Lancaster, K. J. (1966). A new approach to consumer theory, *The Journal of Political Economy* **74**(2): 132–157.
- McFadden, D. L. and Train, K. E. (2000). Mixed MNL models for discrete response, *Journal of Applied Econometrics* **15**: 447–470.
- Rigby, D. and Burton, M. (2006). Modeling disinterest and dislike: a bounded bayesian mixed logit model of the uk market for gm food, *Environmental and Resource Economics* **33**: 485–509.
- Samuelson, W. and Zeckhauser, R. (1988). Status-quo bias in decision-making, *Journal of Risk and Uncertainty* **24**: 7–59.
- Scarpa, R., Ferrini, S. and Willis, K. G. (2005). Performance of error component models for status-quo effects in choice experiments, in R. Scarpa and A. Alberini (eds), *Applications of simulation methods in environmental and resource economics*, Springer, Dordrecht, pp. 247–273.
- Scarpa, R. and Rose, J. M. (2008). Designs efficiency for nonmarket valuation with choice modelling: how to measure it, what to report and why, *Australian Journal of Agricultural and Resource Economics* **52**: 253–282.
- Scarpa, R., Willis, K. G. and Acutt, M. (2007). Valuing externalities from water supply: Status quo, choice complexity and individual random effects in panel kernel logit analysis of choice experiments, *Journal of Environmental Planning and Management* **50**: 449–466.