Position Bias in Best-worst Scaling Surveys: A Case Study on Trust in Institutions

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This paper investigates the effect of items' physical position in the best-worst scaling technique. Although the best-worst scaling technique has been widely used in many fields, the literature has largely overlooked the phenomenon of consumers' adoption of processing strategies while making their best-worst choices. We examine this issue in the context of consumers' trust in institutions to provide information about a new food technology, nanotechnology, and its use in food processing. Our results show that approximately half of the consumers used position as a schematic cue when making choices. We find the position bias was particularly strong when consumers chose their most trustworthy institution compared to their least trustworthy institution. In light of our findings, we recommend that researchers in the field be aware of the possibility of position bias when designing best-worst scaling surveys. We also encourage researchers who have already collected best-worst data to investigate whether their data shows such heuristics.

Key words: Best-worst scaling, position bias, consumer trust, multinomial logit model, latent class logit model, nanotechnology.

JEL codes: C25, D12, Q18.

A cause for concern in stated choice experiments is that respondents exhibit a decision rule or processing strategy while making choices. A number of these processing strategies have been studied in the stated preference literature, mainly in discrete choice experiments. These strategies include attribute non-attendance (Hensher, Rose, and Greene 2005; Campbell, Hutchinson, and Scarpa 2008; Scarpa et al. 2013; Mørkbak, Olsen, and Campbell 2014), attribute-level non-attendance (Erdem, Campbell, and Hole 2014), elimination- and selection-by aspects (Campbell, Hensher, and Scarpa 2012; Erdem, Campbell, and Thompson 2014; Campbell, Hensher, and Scarpa 2014), and ordering effects (Day et al. 2012; Carson, Mørkbak, and Olsen 2012). This paper is motivated by the question of whether some of these issues discovered in other stated preference methods are also present in best-worst scaling (BWS), which was developed by Finn and Louviere (1992) and colleagues.

Although the BWS has been around for some time, it is only recently that we have witnessed its widespread application in a number of disciplines, including agriculture (e.g., Lusk and Briggeman 2009; Erdem, Rigby, and Wossink 2012), environmental studies (e.g., Scarpa et al. 2011), health (e.g., Louviere and Flynn 2011), and marketing (e.g., Cohen 2009). The BWS technique involves respondents choosing two items in a subset of a large list where terms are arranged according to importance (e.g., best and worst, or most and least important). More about the technique and recent examples can be found in Flynn et al. (2007), Lusk and Briggeman (2009), Scarpa et al. (2011), and Erdem and Rigby (2013).

In this paper, we examine whether respondents use item position as a schematic cue when making best-worst choices. We investigate the extent to which the probability of an alternative being chosen depends not only on its item, but also on its position in the choice task. Our paper is motivated by the fact that failing to recognize this phenomenon has

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Amer. J. Agr. Econ. 97(2): 526–545; doi: 10.1093/ajae/aau112
Published online January 20, 2015

implications for choice predictions, and could have serious repercussions for policy recommendations. In particular, models that do not correctly address actual choice behavior will be less useful for priority-setting, and will ultimately hinder efficient policy making. To identify the extent of this issue and to address it, this paper recommends the use of position-specific constants alongside models accommodating a number of latent classes, where the classes are typified by preference heterogeneity and/or position effects.

The empirical case study detailed in this paper focuses on a sample of UK consumers' trust in agents and organizations, and aims to provide balanced and accurate information about nanotechnology and its use in food production. Given the contentious history of recent food-related technologies, for example, genetic modification and irradiation, it is crucial to understand whom consumers trust the most and the least regarding information about emerging food technologies such as nanotechnology and its implementation. Such information may help explain the public's attitude towards accepting the technology, which may then affect its adoption in the industry. The case study makes an important contribution in this area.

Overall, our findings show that: (1) the choices made by around half of our sample (who are more likely to be female, older, and educated) were not sensitive to any position bias; (2) the probability of an institution being chosen depends not only on the institution itself, but also on its position in the BWS choice task (especially among males and respondents who are younger and less educated); (3) the institution positioned at the top of the choice task stands a significantly higher chance of been identified as the most trustworthy; and (4) not accommodating for position bias has significant implications on choice predictions, priority-setting, and the model fit.

The remainder of the paper is structured as follows. In the next section we provide a brief background on position effects. We describe our methodology, as well as the modeling approach for exploring these position effects, or biases, and preference heterogeneity in section three. In section four, we outline our empirical case study, BWS data, and survey design. The main results are reported in section five, followed by the final section, which concludes the paper.

Position Effects

An extensive body of literature in consumer research and marketing and psychology has shown that the manner in which people perceive items, people, or goods often depends on their physical ordering. This includes "edge avoidance" (Rubinstein, Tversky, and Heller 1997), "centrality preferences" (Shaw et al. 2000), "middle bias" (Attali and Bar-Hillel 2003), as well as "center-stage effect" (Valenzuela and Raghubir 2009). The situations where these position effects, or biases, have been identified are varied, and include the following: the ordering of response alternatives in multiple-choice tests (Attali and Bar-Hillel 2003); the allocation of shelf-space in supermarkets (Inman, McAlister, and Hoyer 1990; Wright 2002; Meier and Robinson 2004; Valenzuela and Raghubir 2009); the placement of people (McArthur and Post 1977; Raghubir and Valenzuela 2006; Rodway, Schepman, and Lambert 2013); and items (e.g., products) (Valenzuela and Raghubir 2009; Guney 2014). In these situations, the effects are exhibited in both the "horizontal dimension of space" (see Nisbett and Wilson 1977; Valenzuela, Raghubir, and Mitakakis 2013) and "vertical dimension of space" (see Meier and Robinson 2004; Koppell and Steen 2004; Schubert 2005; Dayan and Bar-Hillel 2011).

In the horizontal dimension of space, it has been repeatedly shown that the arrangement of products from left to right influences consumers' perception of value, their judgments, and ultimately their purchase decisions (e.g., see Raghubir and Valenzuela 2006; Chandon et al. 2009; Valenzuela and Raghubir 2009). Specifically, findings in Chandon et al. (2009) and Valenzuela, Raghubir, and Mitakakis (2013) revealed that consumers perceive products positioned in the center of a shelf as being more popular, premium, or promoted products. Similar effects are observed in other contexts. For example, using six different case studies, Raghubir and Valenzuela (2006) ascertained a strong "center-stage" influence. These authors' research revealed that people often judged the person in a central position as being more important, a better performer, or more likely to be successful. Raghubir and Valenzuela acknowledged that this heuristic may be due to salience effects (i.e., stimulus that makes it stand apart from other similar stimuli due to its inherent characteristics), attributional effects (i.e., better performers often chose positions that are more salient and more likely to be evaluated more favorably), and social norms (i.e., more prominent people sit in the middle of the table; McArthur and Post 1977).

Connotations and associations of vertical space are in widespread metaphoric use in our daily life (e.g., "on top of things," "high points," "thumbs up/down," "hitting rock bottom," and "climbing the corporate ladder"), where the vertical dimension of space influences perceptions of value. Not surprisingly, several studies in the fields of marketing and psychology have sought to investigate the issue. The overwhelming evidence from these studies is that items or products located at the top (or higher) are perceived to be "better" or evaluated more positively than those placed at the bottom (or lower; e.g., Meier et al. 2007; Valenzuela and Raghubir 2010; Valenzuela, Raghubir, and Mitakakis 2013). These are also referred to as primacy and recency order effects. For example, Chandon et al. (2009) found that products on the top and middle shelves gain more attention compared to those on the bottom shelf, and discovered that the effects of vertical position are stronger than any left versus right effect. Again, the influence of vertical positioning goes beyond marketing. For instance, research by Meier and Robinson (2004) has demonstrated that "positive" words are recognized faster when they were placed at the top of the screen, whereas the recognition of "negative" words is stronger when they were placed at the bottom of the screen.

Vertical position is also often linked with the notion of power and seniority. The findings in Schubert (2005) revealed that group labels are typically perceived as being more powerful when they were placed at the top of the screen relative to the bottom of the screen. This is also exemplified in corporate organizational charts, where the CEO is located at the top of the chart, followed by directors, managers, and other employees in the hierarchy.

Horizontal and vertical position effects do not necessarily work in isolation. For example, Valenzuela, Raghubir, and Mitakakis (2013) found that retailers place the premium brand on the top, the cheapest brand on the bottom, the most popular brand in the center, products in promotion at the horizontal extremes (like in Inman, McAlister, and Hoyer 1990), and store brands next to promoted and popular brands in the center.

With the knowledge that position is a commonly employed heuristic, researchers have looked into whether it can be used for nudging people towards healthier decisions by exploring the position effect on food menus (e.g., Dayan and Bar-Hillel 2011) and shelf position of healthy and unhealthy foods (e.g., van Kleef, Otten, and van Trijp 2012; Rozin et al. 2011).

In this paper, we focus on the vertical position effect in a BWS survey. The BWS data is particularly well-suited to exploring this position bias due to the nature of BWS tasks asking respondents to identify their "best" and "worst" choices among a subset of a large list of items. In the following section, we describe how we identify and accommodate for this position bias.

Methodology

We start this section by providing a brief description of the BWS technique. We follow this by introducing the necessary notation and a basic model for analyzing the BWS data. Then we expand on this base model to uncover the role of an item's position on its likelihood of being chosen as best and worst, and by making provision for preference heterogeneity.

The Best-worst Scaling Method

While people can usually comfortably rank a small list of items, as the list of items that are to be ranked increases, the ranking task becomes more cognitively challenging and, importantly, susceptible to a range of anomalous behaviors. The BWS technique avoids this by breaking tasks into more manageable sizes, thereby reducing—if not eliminating—difficulty in ranking the full list of items in terms of their importance (or preferability). Furthermore, as respondents only choose at the extreme (i.e., best/worst or most/least), the process is considered to be "scale-free" and prevents a scale-use bias (Baumgartner and Steenkamp 2001). For example, when using a likert scale for identifying respondents' level of preferences, there may be situations where respondents may only focus on one part of the scale. Moreover, there may be cases where respondents have difficulty in distinguishing the differences between the levels of the scale. For example, the difference between "strongly agree" and "agree" may be difficult to identify. This creates an ambiguity in the interpretation of these scale levels across respondents. In BWS, however, such ambiguity is absent, as only extremes are needed to be identified in a subset of items. There is also evidence that people use better judgment when they only need to identify the extremes, rather than preferences with levels (Louviere 1993; Marley and Louviere 2005).

The BWS approach has been used, and shown to be suitable, in a number of research areas to assess people's perception of intangible concepts. For example, Erdem and Rigby (2013) examined the general public's perception of control and worry over various risks; Erdem, Rigby, and Wossink (2012) looked at consumer perception of relative responsibility for ensuring food safety; Louviere and Flynn (2011) examined the public's perception and preferences for healthcare reform in Australia; and Auger, Devinney, and Louviere (2007) investigated the attitudes of consumers towards social and ethical issues such as recycling and human rights, across six countries.

Basic Model and Background Notation

The BWS is an application of the random utility maximization theory (Manski 1977; Thurstone 1927), whereby respondents evaluate all possible pairs of items within the displayed BWS task and choose the pair that reflects their maximum difference in preference. The number of unique pairs, J, is given by $S(S-1)$, where S represents the number of items in the BWS task. Overall utility, U, associated with respondent n's chosen pair, i, in BWS task t is given by the difference in utility between the best and worst items:

$$(1) \qquad U_{nit} = \underbrace{(\beta x_{b_{nit}})}_{\text{Best}} - \underbrace{(\beta x_{w_{nit}})}_{\text{Worst}} + \varepsilon_{nit}$$

where β is a vector of estimated parameters (subject to $\sum_{k=1}^{K} \beta_k = 0$) relating to the best and worst items, x (indexed by b and w respectively), and ε is an *iid* type I extreme value (EV1) distributed error term, with constant variance of $\pi^2/6$. Given these assumptions, the probability of the sequence of best-worst choices made by individual n can be represented by the multinomial logit (MNL) model:

$$(2) \qquad \Pr(y_n|x_n) = \prod_{t=1}^{T_n} \frac{\exp((\beta x_{b_{nit}}) - (\beta x_{w_{nit}}))}{\sum_{j=1}^{J} \exp((\beta x_{b_{njt}}) - (\beta x_{w_{njt}}))}$$

where y_n gives the sequence of best-worst choices over the T_n BWS tasks for respondent n, that is, $y_n = [i_{n1}, i_{n2}, \ldots, i_{nT_n}]$.[1]

The vector of estimated parameters, β, are on an interval scale and typically consist of both negative and positive values, making interpretation difficult. For this reason, similar to Erdem and Rigby (2013), it is useful to convert the raw coefficients, which are zero-centered, to ratio-scaled probabilities, which we denote using $\overset{*}{\Pr}(x)$. For item k, the conversion to a 0–100 point ratio scale is achieved as follows:

$$(3) \qquad \overset{*}{\Pr}(x_k) = \left(\frac{\exp(\beta_k)}{\exp(\beta_k) + S - 1} \Bigg/ \sum_{k=1}^{K} \frac{\exp(\beta_k)}{\exp(\beta_k) + S - 1} \right) \times 100$$

where S, as previously defined, is the number of items shown per choice task. These ratio-scaled probabilities provide an intuitive interpretation, since we can say that an item with a score of 20 is twice as preferred or important as an item with a score of 10.

Accounting for Position Bias

The choice probability retrieved from expression (2) assumes that all respondents consider all offered items and the likelihood of best and worst choices are independent from their position. However, it is important to recognize that the probability of choice may depend not only on utility, but also on an item's location. In particular, in line with evidence found in the papers discussed above, one could postulate that position acts as a schematic cue that leads to systematic biases in respondents' decisions. For example, when choosing the item that provides them with

[1] We note that accounting for the panel effect is immaterial in the MNL model due to the independence of choice probabilities. We nevertheless present the MNL model in this manner to introduce the necessary terms as early on as possible so that differences in models are clearer as we progress through this section.

the greatest utility, respondents may be more inclined to choose among the options located closer to the top (or left) of the choice task. In contrast, the item they indicate as being the worst has a tendency to be located closer to the bottom (or right) of the choice task.

Failing to account for this vertical or horizontal position bias could lead to misguided inferences, as the model does not reflect actual choice behavior. A straightforward approach for addressing this phenomenon is to introduce position-specific constants into the utility function as follows:

$$(4)\quad \Pr(y_n|x_n) = \prod_{t=1}^{T_n} \frac{\exp((\beta x_{b_{nit}} + \gamma_{b_{nit}}) - (\beta x_{w_{nit}} + \gamma_{w_{nit}}))}{\sum_{j=1}^{J} \exp((\beta x_{b_{njt}} + \gamma_{b_{njt}}) - (\beta x_{w_{njt}} + \gamma_{w_{njt}}))}$$

where the γ terms denote the position-specific constants, which capture the average effect on utility of all factors that are not included in the model.[2] In cases where there are no systematic differences due to item position, we should expect $\gamma = 0$. However, in situations where item position has a bearing on choice outcomes (either negative or positive), we can expect to find $\gamma \neq 0$. Note that the γ terms are indexed by either b or w to distinguish the role of position on best and worst choices, respectively. For identification purposes, the values of γ_b and γ_w are subject to the constraint $\sum_{s=1}^{S} \gamma_{b_s} = 0$ and $\sum_{s=1}^{S} \gamma_{w_s} = 0$, respectively, meaning that they are zero-centered and are also suitable for probability-based rescaling.

The introduction of position-specific constants represents a first step in uncovering the systematic impact of item position on best and worst choices. Nevertheless, a concern remains that the results could be biased by a subset of respondents who entirely overlooked the items, but made their choices based purely on the item's position. In the same vein, there may be another subset of respondents who consistently disregarded the position and made choices that were solely driven by the items themselves. Suggesting the adoption of these different processing strategies is equivalent to identifying three separate classes of choice behavior among respondents: 1) a class in which the choices reflect the preferences of the items in the BWS survey; 2) a class where both preferences and position influenced choice outcomes; and 3) a class in which the choices are entirely a result of schematic cues based on the item's position within the choice task.

Respectively, the utility functions associated with these three classes can be described by:

$$(5a)\quad V_{1_{nit}} = (\beta x_{b_{nit}} + \gamma_{b_{nit}}) - (\beta x_{w_{nit}} + \gamma_{w_{nit}}),$$

$$(5b)\quad V_{2_{nit}} = (\beta x_{b_{nit}}) - (\beta x_{w_{nit}}), \text{ and}$$

$$(5c)\quad V_{3_{nit}} = (\gamma_{b_{nit}}) - (\gamma_{w_{nit}})$$

where V_c represents the observable part of utility associated with class c. While deciding the number of processing strategies to accommodate is an empirical consideration, the actual choice process used by respondents remains latent. To work around this, based on observed choice behavior, probabilistic conditions can be imposed on the utility expressions in (5). In doing so, the presence of processing strategies can be established up to a probability, with the full probability per respondent allocated across all C classes. Under this framework, the probability of best-worst choice can be represented as follows:

$$(6)\quad \Pr(y_n|x_n) = \sum_{c=1}^{C} \pi_c \prod_{t=1}^{T_n} \frac{\exp(V_{c_{nit}})}{\sum_{j=1}^{J} \exp(V_{c_{njt}})}$$

where π_c denotes the unconditional probabilities associated with observing the utility function relating to class c (i.e., the likelihood of competing processing strategies being their actual strategy).

Accounting for Heterogeneous Preferences and Processing Strategies

The model described in equation (6) accommodates respondents with different utility functions and, to avoid confounding between heterogeneity in preferences and processing, equality constraints (see Scarpa et al. 2009) are imposed on β in expressions (5a)

[2] Note that these position-specific constants are analogous to the alternative-specific constants that are routinely used in discrete choice modeling. However, in our case, the alternative-specific constants are effectively the difference between the relevant pair of position-specific constants for the best and worst choices.

and (5*b*), as well as for γ in (5*a*) and (5*c*). This model is based on the assumption that all respondents have the same preferences and/or are equally influenced by position. For a variety of reasons, most empirical evidence reveals heterogeneity rather than homogeneity across respondents. Therefore, we treat each of the β and γ parameters as finitely distributed random terms, now denoted with the subscript c (i.e., β_c and γ_c, respectively), to represent classes with heterogeneous preferences and processing strategies. For example, if we assume that there are two segments in the population, both of which have their own preferences, and that there are also two segments in the population, both of which exhibit different position effects, then six utility expressions—and, hence, latent classes—initially come to mind:

$$(7a)\quad V_{1_{nit}} = (\beta_1 x_{b_{nit}} + \gamma 1_{b_{nit}}) - (\beta_1 x_{w_{nit}} + \gamma 1_{w_{nit}});$$

$$(7b)\quad V_{2_{nit}} = (\beta_1 x_{b_{nit}}) - (\beta_1 x_{w_{nit}});$$

$$(7c)\quad V_{3_{nit}} = (\gamma 1_{b_{nit}}) - (\gamma 1_{w_{nit}});$$

$$(7d)\quad V_{4_{nit}} = (\beta_2 x_{b_{nit}} + \gamma 2_{b_{nit}}) - (\beta_2 x_{w_{nit}} + \gamma 2_{w_{nit}});$$

$$(7e)\quad V_{5_{nit}} = (\beta_2 x_{b_{nit}}) - (\beta_2 x_{w_{nit}}); \text{ and}$$

$$(7f)\quad V_{6_{nit}} = (\gamma 2_{b_{nit}}) - (\gamma 2_{w_{nit}}).$$

In addition to the above, we should recognize that for some respondents estimated as having β_1, their position effects may be best described using γ_2 and, similarly, the possibility that the position effects characterized by γ_1 may have been exhibited by respondents with the item coefficients β_2. Therefore, it is important to recognize two further classes:

$$(7g)\quad V_{7_{nit}} = (\beta_1 x_{b_{nit}} + \gamma 2_{b_{nit}}) - (\beta_1 x_{w_{nit}} + \gamma 2_{w_{nit}});$$

$$(7h)\quad V_{8_{nit}} = (\beta_2 x_{b_{nit}} + \gamma 1_{b_{nit}}) - (\beta_2 x_{w_{nit}} + \gamma 1_{w_{nit}}).$$

Including (7*g*) and (7*h*) means that we are in a better position to jointly identify the marginal utilities and position influences. This is important since it goes some way towards alleviating the risk of confounding (see Campbell, Hensher, and Scarpa 2012; Hensher, Collins, and Greene 2012; and Hess et al. 2012, for a discussion on this issue). Once again, the probabilities associated with the above eight representative utility functions, as well as the segment-specific vector of βs and γs, can be derived using equation (6), where $C = 8$.

Data

The BWS data is obtained from an empirical case study that investigates consumers' trust in institutions to provide accurate and balanced information regarding the use of nanotechnology and its use in food production. Overall, we used 16 institutions, ranging from government institutions to the media, friends, and family. Table 1 shows the institutions included in the BWS survey.

Survey design plays an important role in obtaining reliable responses. In our survey, each respondent was presented with five institutions in each of eight BWS choice tasks. For each choice task, they were asked to indicate the "most" and "least" trustworthy institutions among the presented subset of institutions. Figure 1 illustrates a typical BWS task presented to the respondents. Given that the total number of items used in the survey is quite large, we felt that it is plausible to use five items in each choice task. This decision was also driven by feedback from the pilot study, as well as evidence that showing more than five items to respondents may result in confusion and fatigue (e.g., see Cohen and Orme 2004), which may, in turn, result in unreliable responses.

The experimental design comprised of 300 versions (i.e., blocks) to avoid any context and ordering based biases. In each BWS choice task, different combinations of five institutions were shown to respondents. The combinations of five institutions in these choice tasks satisfy the optimal design characteristics: frequency balance; orthogonality; positional balance; and connectivity among tasks within and across each block. That is, the one-way frequencies reveal that the survey design was perfectly balanced as each item in the survey was displayed 750 times across all versions of the surveys.[3] The two-way frequencies show that the survey had a nearly orthogonal main-effects design, in which each item appeared an average of 200 times with every other item, with a standard deviation of 0.51. The positional frequencies show that each item, on average, appeared 150 times at each position (i.e., first, second,

[3] As five items are presented in each set, overall there were 40 items shown in every version (i.e., 5 items times 8 tasks). As there are 16 institutions in total, each institution appeared approximately 2.5 times in each version. Across all 300 versions, each institution appears 750 times.

Table 1. Institutions and Agents Included in the Best-worst Scaling Study

Item	Institution/agent	Coding in model output
Government institutions		
1	Department for Environment, Food, and Rural Affairs	DEFRA
2	Food Standards Agency	FSA
3	Department of Health	DH
Scientists		
4	Food industry scientists	FoodIndSci
5	University scientists	UniSci
Non-government organizations		
6	Consumer organizations (e.g., Which?, National Consumer Federation, etc.)	ConsumOrg
7	Environmental groups (e.g., Greenpeace, Friends of the Earth, etc.)	EnvGrps
Food handlers		
8	Food manufacturers/processors	Manufact
9	Farmers/growers	Farmers
10	Supermarkets	Supermkt
11	High street butchers	Butchers
Friends and family		
12	Friends and family	Friends
Media		
13	TV/radio: news programs	News
14	TV/radio: food and cooking programs	FoodProg
15	Newspapers	NewsPaps
16	Food magazines (e.g., Good Food magazine, Sainsbury's and Tesco's magazines, etc.)	Magazines

Consider the five organisations/people shown below. Please indicate which of the five you:

- Trust **MOST** to provide accurate and balanced information about nanotechnology and its use in food production
- Trust **LEAST** to provide accurate and balanced information about nanotechnology and its use in food production

Trust **most** on nanotechnology		Trust **least** on nanotechnology
○	Newspapers	○
○	Environmental groups	○
○	Farmers/growers	○
○	Food industry scientists	○
○	Food Standards Agency	○

Figure 1. Typical best-best scaling task

third, fourth, and fifth) with a standard deviation of 0.45. After ensuring a balanced and nearly orthogonal survey design, tasks were randomized, and a participant was randomly assigned to a version.

The web-based surveys were conducted with a sample of 616 consumers in the UK in 2010. With each respondent answering 8 BWS tasks, we obtained a total of 4,298 observations for model estimation. The

Table 2. Observed Choices

Best (*s*)	Worst (*s*)	Pair (*j*)	Count	Percentage	95% confidence interval (percent)
1			1136	23.05	21.88–24.23
2			1078	21.88	20.72–23.03
3			909	18.45	17.36–19.53
4			917	18.61	17.52–19.69
5			888	18.02	16.95–19.09
	1		1008	20.45	19.33–21.58
	2		930	18.87	17.78–19.96
	3		910	18.47	17.38–19.55
	4		1038	21.06	19.92–22.20
	5		1042	21.14	20.00–22.28
1	2	1	252	5.11	4.50–5.73
1	3	2	297	6.03	5.36–6.69
1	4	3	304	6.17	5.50–6.84
1	5	4	283	5.74	5.09–6.39
2	1	5	260	5.28	4.65–5.90
2	3	6	219	4.44	3.87–5.02
2	4	7	314	6.37	5.69–7.05
2	5	8	285	5.78	5.13–6.44
3	1	9	261	5.30	4.67–5.92
3	2	10	210	4.26	3.70–4.83
3	4	11	215	4.36	3.79–4.93
3	5	12	223	4.53	3.94–5.11
4	1	13	244	4.95	4.35–5.56
4	2	14	239	4.85	4.25–5.45
4	3	15	183	3.71	3.19–4.24
4	5	16	251	5.09	4.48–5.71
5	1	17	243	4.93	4.33–5.54
5	2	18	229	4.65	4.06–5.23
5	3	19	211	4.28	3.72–4.85
5	4	20	205	4.16	3.60–4.72

majority of the respondents were female (51%), fell in the 18–45 age group (61%), had a school-level education (i.e., up to 18 years of age; 54%), and were employed (51%). The average annual household (gross) income was in the region of £25,000–£30,000. A comparison with the 2011 UK census data shows that the respondents in our study were similar to the general UK population with respect to gender, age, and employment status.

Results

In an attempt to tease out the impact of item position on the BWS choices, we begin this section with a rudimentary examination of the choices made by individuals. Following this, we report results from our econometric models and post-estimation analysis.

Examination of Choices

As a first step in assessing the role that item position had on choices in the BWS exercise, we test the H_0 that, other things being held constant, there is no association between the set of observed counts of best and worst choices in each position and their expected counts. If there is no ordering effect, each position should be chosen an equal number of times as the best and worst option. Given that there were five items per choice task (i.e., $S = 5$) and our dataset consists of 4,928 choice observations, this would equate to an expected breakdown of 985.6 (i.e., 20%) best and worst choices per position and 246.4 (i.e., 5%) for each combination of best-worst choices. Table 2 presents the actual distribution of choices.

Examining the positional spread of best choices in table 2, there appears to be some deviations between the observed and expected distributions. Notably, all else being equal, there is seemingly clear evidence that institutions located closer to the top of the BWS choice task have a significantly higher likelihood of being chosen as best (in this case, most trustworthy), which accords with findings in Valenzuela, Raghubir, and Mitakakis (2013). Indeed, with a χ^2 test statistic of 52.006, against the critical value of 9.488 ($\chi^2_{0.05,4}$), we can reject the H_0 that, *ceteris paribus*, the institutions identified as being most trustworthy were not subject to a position bias.

It is interesting to note that as we move our attention to the distribution of worst choices (in this case, least trustworthy), we find the opposite finding—other things being constant, institutions located closer to the bottom of the choice task were more likely to be identified as being least trustworthy. While the pattern is not as striking, the χ^2 test statistic of 15.458 (against the same critical value of 9.488 ($\chi^2_{0.05,4}$)), does, nevertheless, point towards a significant ordering effect.

Taking this analysis further, we also compare the 20 best-worst choice combinations. In this case, we again find that the χ^2 test statistic of 100.239 exceeds the critical value of 30.144 ($\chi^2_{0.05,19}$). This provides further compelling evidence to support the rejection of the H_0 in favor of the H_1, where position plays an influential role on the choices made by respondents.

Estimation Results

While breaking down the choices and nonparametric test statistics might provide the first clue of position bias, they cannot rule out experimental design artifacts relating to the location of the trust items. For this reason, we turn to the results of the models described in the methodology section. We present these results in table 3. All models were coded and estimated in Ox version 6.2 (see Doornik 2009, for further details) using maximum likelihood estimation.[4] For each model, we separately report the estimated trust coefficients for the institutions used in the BWS survey and position-specific constants—where, for normalization, the final item (food magazines) and position $s = 5$ are arbitrarily set to the base level (i.e., the negative sum of their respective coefficients) and, therefore, are omitted from the table. Class membership probabilities, where applicable, along with model fit and diagnostic statistics, are also provided in the table.

As a point of reference, our analysis starts with the MNL model with position-specific constants, as specified in expression (4).[5] Looking firstly at the results of this model, we observe that on average, respondents are more likely to trust communication on nanotechnology and its use in food production from government institutions and scientists compared to non-government organizations, food handlers, friends and family, and the media. To ease the interpretation, we provide the ratio-scaled probabilities, as described in equation (3) in table 4. For instance, this reveals that, under the MNL model, the information coming from the Food Standard Agency is, on average, considered to be more than seven times more trustworthy compared to information provided in newspapers (i.e., 13.94/1.97).

The position-specific constants retrieved under our first model provide an important insight into position effects. Firstly, we draw attention to the fact that they are non-zero, and importantly, in most instances the deviations from zero are statistically significant—meaning that we reject the H_0 that there are no systematic differences due to item position. Moreover, the position-specific constants differing between the best and the worst choices also signifies that the schematic cues stemming from an item's position are not the same for best and worst choices. Notably, the values of the position-specific constants for the best choices (γ_b) are of a higher magnitude compared to those obtained for the worst choices (γ_w)—implying that, other things remaining constant, the position bias is stronger for the best choices compared to the worst choices. Interestingly, in accordance with the pattern of observed best choices in table 2, there is a reduction in the position-specific

[4] In the case of the models that retrieve class probabilities, we are mindful of their vulnerability to local maxima of the sample-likelihood function. Thus, in an attempt to reduce the possibility of reaching a local, rather than a global maximum, we started the estimation iterations from a variety of random starting points. Specifically, we do this by estimating these models many times, but each time using a different vector of starting values, which are chosen randomly.

[5] For the sake of brevity, we do not report the MNL model without position-specific constants, nor the MNL with only position-specific constants. With log-likelihood values of −12,495.56 and −14,728.66, respectively (versus a null log-likelihood of −14,762.97), these were both found to be inferior to our reference model in table 3, which is associated with a log-likelihood of −12,455.82.

Table 3. Estimation Results

	MNL		LC1		LC2				LC3			
LL	−12,455.82		−11,818.46		−11,687.46				−11,478.93			
K	23		25		47				53			
$\bar{\rho}^2$	0.155		0.198		0.205				0.219			
AIC	24,957.64		23,686.91		23,468.92				23,063.87			
BIC	25,107.20		23,849.48		23,774.55				23,408.51			
Trust coefficients												
	$\hat{\beta}_1$	|*t*–rat.|	$\hat{\beta}_1$	|*t*–rat.|	$\hat{\beta}_1$	|*t*–rat.|	$\hat{\beta}_2$	|*t*–rat.|	$\hat{\beta}_1$	|*t*–rat.|	$\hat{\beta}_2$	|*t*–rat.|
Government institutions												
EFRA	0.89	20.71	1.68	25.34	1.87	24.53	−0.05	0.61	1.95	23.58	0.95	6.91
FSA	1.41	31.52	2.41	34.12	2.64	31.63	0.25	3.17	2.78	32.59	1.33	9.08
DH	0.98	22.53	1.79	26.55	1.96	25.45	0.05	0.68	2.07	25.07	0.85	5.99
Scientists												
FoodIndSci	0.68	15.92	1.29	19.65	1.53	19.48	−0.13	1.81	1.82	22.68	−0.47	2.91
UniSci	0.85	19.84	1.42	21.63	1.51	21.09	0.35	4.80	1.52	18.68	1.33	9.77
Non-government organizations												
ConsumOrg	0.77	17.93	1.09	17.50	1.01	14.68	0.76	9.90	0.89	10.75	1.97	14.19
EnvGrps	−0.11	2.70	−0.38	6.12	−0.63	8.53	0.44	5.89	−0.89	11.65	1.40	9.60
Food handlers												
Manufact	−0.76	17.90	−1.15	19.12	−1.09	16.36	−0.61	8.06	−0.87	10.50	−2.51	16.04
Farmers	−0.14	3.40	−0.39	6.44	−0.46	7.07	0.15	2.01	−0.42	5.43	−0.18	1.12
Supermkt	−0.88	20.55	−1.37	23.39	−1.39	21.46	−0.46	6.26	−1.31	18.15	−1.89	13.86
Butchers	−0.35	8.33	−0.78	12.79	−0.93	13.98	0.21	2.83	−0.95	12.70	−0.24	1.38
Friends and family												
Friends	−0.73	17.17	−1.39	22.83	−1.56	23.53	0.16	2.15	−1.66	23.37	−0.53	3.29
Media												
News	−0.51	12.09	−0.88	14.96	−0.93	14.21	−0.19	2.58	−1.07	15.16	−0.18	1.50
FoodProg	−0.52	12.27	−0.84	14.42	−0.91	14.40	−0.25	3.58	−1.02	14.76	−0.32	2.72
NewsPaps	−1.18	27.27	−1.79	29.60	−1.87	28.17	−0.56	7.66	−2.02	26.46	−1.13	9.24
Position-specific constants												
	$\hat{\gamma}_1$	|*t*–rat.|	$\hat{\gamma}_1$	|*t*–rat.|	$\hat{\gamma}_1$	|*t*–rat.|	$\hat{\gamma}_2$	|*t*–rat.|	$\hat{\gamma}_1$	|*t*–rat.|	$\hat{\gamma}_2$	|*t*–rat.|
Best												
γ_{b_1}	0.19	6.23	0.36	7.01	0.14	3.02	0.31	5.98	1.14	5.51	0.25	3.12
γ_{b_2}	0.10	3.22	0.21	4.13	0.04	0.87	0.19	3.82	1.07	5.38	0.10	1.28
γ_{b_3}	−0.10	3.02	−0.14	2.56	−0.08	1.81	−0.11	1.93	0.22	1.03	−0.13	1.91
γ_{b_4}	−0.07	2.32	−0.13	2.21	−0.05	1.00	−0.10	1.84	−0.92	2.22	−0.03	0.48
Worst												
γ_{w_1}	−0.07	2.12	−0.16	2.95	−0.06	1.55	−0.12	2.13	0.16	0.75	−0.23	3.12
γ_{w_2}	0.05	1.68	0.17	2.93	−0.01	0.16	0.18	3.14	0.16	0.69	0.14	1.84
γ_{w_3}	0.11	3.38	0.16	3.02	0.12	2.89	0.08	1.47	−0.31	1.92	0.29	3.80
γ_{w_4}	−0.05	1.54	−0.15	2.91	0.04	1.06	−0.17	3.42	−0.48	4.11	−0.05	0.78
Unconditional class membership probabilities												
	$\hat{\pi}$	|*t*–rat.|	$\hat{\pi}$	|*t*–rat.|		$\hat{\pi}$	|*t*–rat.|			$\hat{\pi}$	|*t*–rat.|	
$\pi_{\beta_1\gamma_1}$	1.00	fixed	0.19	2.98		0.66	18.97			0.01	1.02	
π_{β_1}			0.53	7.58						0.36	4.34	
π_{γ_1}			0.27	12.09						0.06	3.76	
$\pi_{\beta_2\gamma_2}$						0.34	12.84			0.06	1.48	
π_{β_2}										0.14	3.14	
π_{γ_2}										0.16	7.74	
$\pi_{\beta_1\gamma_2}$										0.21	2.62	
$\pi_{\beta_2\gamma_1}$										0.00	0.00	

Table 4. Ratio-scaled Probabilities

	MNL	LC1		LC2			LC3		
x	$\overset{*}{\Pr}(x)$	$\overset{*}{\Pr}(x\|\beta_1)$	$\mathbb{E}\left(\overset{*}{\Pr}(x)\right)$	$\overset{*}{\Pr}(x\|\beta_1)$	$\overset{*}{\Pr}(x\|\beta_2)$	$\mathbb{E}\left(\overset{*}{\Pr}(x)\right)$	$\overset{*}{\Pr}(x\|\beta_1)$	$\overset{*}{\Pr}(x\|\beta_2)$	$\mathbb{E}\left(\overset{*}{\Pr}(x)\right)$
Government institutions									
DEFRA	10.45***	13.50***	10.10***	14.17***	5.84	11.36***	14.30***	9.60***	11.55***
FSA	13.94***	17.30***	12.12***	17.81***	7.35**	14.28***	18.02***	11.86***	14.14***
DH	11.00***	14.08***	10.41***	14.65***	6.31	11.83***	14.97***	9.04***	11.82***
Scientists									
FoodIndSci	9.12***	11.21***	8.88***	12.24***	5.45**	9.95***	13.65***	3.31***	9.91***
UniSci	10.20***	11.97***	9.29***	12.16***	7.95***	10.74***	12.00***	11.87***	10.69***
Non-government organizations									
ConsumOrg	9.66***	10.05***	8.27***	9.35***	10.53***	9.74***	8.52***	15.62***	9.44***
EnvGrps	5.03***	3.43***	4.75***	2.70***	8.48***	4.65***	2.10***	12.30***	5.08**
Food handlers									
Manufact	2.89***	1.72***	3.85***	1.79***	3.61***	2.40***	2.14***	0.49***	2.73***
Farmers	4.90***	3.42***	4.74***	3.12***	6.81	4.36***	3.19***	4.23***	4.08***
Supermkt	2.60***	1.41***	3.68***	1.34***	4.12***	2.28***	1.43***	0.90***	2.40***
Butchers	4.12***	2.42***	4.22***	2.06***	7.15*	3.78***	1.99***	4.03***	3.35***
Friends and family									
Friends	2.97***	1.38***	3.66***	1.14***	6.90*	3.09***	1.02***	3.16***	2.62***
Media									
News	3.59***	2.20***	4.10***	2.05***	5.22***	3.12***	1.77***	4.22***	3.27***
FoodProg	3.57***	2.30***	4.15***	2.09***	4.94***	3.05***	1.86***	3.76***	3.23***
NewsPaps	1.97***	0.94***	3.43***	0.85***	3.80***	1.85***	0.72***	1.83***	2.18***
Magazines	3.99***	2.68***	4.36***	2.48***	5.55	3.51***	2.32***	3.76	3.49***

Note: The Krinsky-Robb (1986) simulation technique (using 100,000 draws) was employed to generate empirical distributions of the parameters, from which the standard errors were constructed (H_0: $\overset{*}{\Pr}(\cdot) = 6.25$ (i.e., 100/16); *p-value ≤ 0.05, **p-value ≤ 0.01 and ***p-value ≤ 0.001).

constants as one moves from the top to the bottom item position. The position-specific constants for the worst choices indicate a somewhat different pattern. While position bias does not seem to have played as strong a role, the estimates do, nonetheless, imply that compared to the uppermost and lowermost items, respondents were slightly less inclined to choose items located in the center when making their worst choices, which is similar to the findings in Dayan and Bar-Hillel (2011). To facilitate the interpretation, we calculate the probability of each combination of pairs being chosen using only the position-specific constants. The retrieved, *ceteris paribus*, best and worst position probabilities are reported in table 5. From these calculations, the position effects predicted under the MNL model are seen more clearly.

Our second model (labeled LC1) is a latent class logit model. In this model, each latent class is described by the set of specific heuristics described in equation (5), rather than a set of marginal class-specific utilities that is more common in latent class models. Firstly, we remark on the large increase in the model fit. Indeed, at the expense of just two additional parameters, we witness an improvement of over 600 log-likelihood units. The magnitude of this increase does provide evidence in favor of simultaneously accounting for the three information processing strategies over the assumption of processing homogeneity. However, we do acknowledge that this improvement is partly due to the fact that the panel nature of the data is being accounted for, making it difficult to truly corroborate this. With an unconditional class membership probability of $\pi_{\beta_1} = 0.53$, more than half of the respondents made their best and worst choices independently from the item's position. Crucially, however, this draws attention to the alarming fact that, for almost half of the respondents, the item's position influenced its likelihood of being chosen.

In addition, we observe that over one-quarter (i.e., $\pi_{\gamma_1} = 0.27$) of respondents are predicted to have made their choices solely based on item position. Scrutinizing the

Table 5. Position Probabilities

	MNL	LC1		LC2			LC3		
s	$\Pr(s)$	$\Pr(s\mid\gamma_1)$	$\mathbb{E}(\Pr(s))$	$\Pr(s\mid\gamma_1)$	$\Pr(s\mid\gamma_2)$	$\mathrm{E}(\Pr(s))$	$\Pr(s\mid\gamma_1)$	$\Pr(s\mid\gamma_2)$	$\mathbb{E}(\Pr(s))$
Best									
1	0.24***	0.27***	0.23***	0.23*	0.26***	0.24***	0.40**	0.24*	0.23***
2	0.22***	0.25***	0.22***	0.21	0.25***	0.22**	0.37***	0.23*	0.22***
3	0.18**	0.18**	0.19*	0.19	0.18*	0.19*	0.14*	0.18	0.19*
4	0.18***	0.16***	0.18***	0.19	0.17***	0.18**	0.05***	0.19	0.18**
5	0.18***	0.14***	0.17***	0.19	0.15***	0.17***	0.04***	0.16*	0.17***
Worst									
1	0.20	0.21	0.20	0.20	0.20	0.20	0.12**	0.23*	0.21
2	0.18**	0.16***	0.18***	0.20	0.16***	0.19*	0.12***	0.17**	0.18***
3	0.18**	0.18**	0.19**	0.18**	0.19	0.18**	0.26*	0.15***	0.18**
4	0.21**	0.24***	0.22***	0.19	0.24***	0.21*	0.35***	0.21	0.21**
5	0.22*	0.22	0.21	0.22*	0.21	0.22*	0.14	0.24*	0.21

Note: The Krinsky-Robb (1986) simulation technique (using 100,000 draws) was employed to generate empirical distributions of the parameters, from which the standard errors were constructed (H_0: $\Pr(\cdot) = 0.2$ (i.e., 1/5); *p-value ≤ 0.05, **p-value ≤ 0.01 and ***p-value ≤ 0.001).

position-specific constants (along with the derived probabilities in table 5) reveals a similar pattern of position bias to that which emerged from the MNL model. We note, however, that in the case of LC1, the estimated position-specific constants only relate to the subset associated with the utility functions given by equations (5*b*) and (5*c*). Within these two classes, as presented in table 5, the top two positions alone account for over half of the best choices (0.27 for the first, 0.25 for the second position). In contrast, the respective figure for the bottom two positions is approximately 30% (0.16 for the fourth, 0.14 for the fifth position). Although, again, position is found to be less influential in the worst choices, we find further supporting evidence of an inclination towards the top and bottom positions.

Our next model (labeled LC2) assumes two latent classes, which differ in terms of the trust coefficients and position-specific constants (i.e., the utility functions represented by equations (7*a*) and (7*d*)). This model attains a superior fit as compared to the MNL and LC1 models. Although estimating separate trust coefficients and position-specific constants for each class comes at a very high parametric cost, the $\bar{\rho}^2$, as well as both information criteria, confirm this finding even after accounting for the loss of parsimony. We find that the main differences in the trust coefficients and ratio-scaled probabilities between the first and second latent classes (which are associated with unconditional class membership probabilities of $\pi_{\beta_1\gamma_1} = 0.66$ and $\pi_{\beta_2\gamma_2} = 0.34$, respectively) are the level of trust placed on communication from government institutions and scientists.[6] Other things being equal, whereas the first class considers information originating from these institutions to be highly trustworthy (ratio-scaled probabilities in the range 12–18), the second class considers the information relatively less reliable (ratio-scaled probabilities in the range 5–8). The second class appears to deem communications on nanotechnology relatively more trustworthy when it originates from friends and family, as well as media sources.

Focusing on the position-specific constants for the best choices, we again discover that the average effect on utility declines as we move from the top item position to the bottom item position. Interestingly, this same position bias is manifested in both latent classes, though it appears to be more perceptible and statistically significant in the second class. We also find the position effect in worst choices. The effect is quite similar in both classes and broadly consistent with that uncovered in the previous models.

Our final model (labeled LC3) is a further latent class logit model combining features of LC1 and LC2 that simultaneously accounts

[6] We acknowledge that the conversion to ratio-scaled probabilities does not factor out the scaling of the parameter estimates that is related to the scale factor of the unobserved Gumbel error component. In each of our models (and latent classes) these scale parameters are normalized (essentially to 1.0), which we admit thereby prevents any meaningful comparison of parameter estimates and ratio-scaled probabilities between models (and classes). Notwithstanding this limitation, we feel that the ratio-scaled probabilities do nevertheless provide a valuable insight into how position bias and the manner in which it is addressed has an impact on the model outputs.

for position effect and trust heterogeneity by allowing for all eight utility expressions in equation (7). As expected, LC3 is associated with the best model fit. This is corroborated by all of the diagnostic statistics that account for the increase in estimated parameters. The trust coefficients and ratio-scaled probabilities correspond reasonably well to those retrieved under LC2.

Relatively speaking, classes associated with $\hat{\beta}_1$ (with an aggregate unconditional class membership probability of $\pi_{\beta_1} + \pi_{\beta_1\gamma_1} + \pi_{\beta_1\gamma_2} = 0.58$) once more perceive government institutions and scientists as more trustworthy than other institutions. Classes estimated with $\hat{\beta}_2$ (with an aggregate unconditional class membership probability of $\pi_{\beta_2} + \pi_{\beta_2\gamma_2} + \pi_{\beta_2\gamma_1} = 0.20$), however, again favor information from friends and family, non-government organizations, and media sources. Indeed, comparing these groups of consumers, the first group considers information from food industry scientists to be, on average, 19 times more trustworthy compared to information provided in newspapers (i.e., 13.65/0.72), whereas the second groups deem the information to be less than two times as trustworthy (i.e., 3.31/1.83).

Of central interest in this paper is the effect of position on consumers' choices in the BWS survey. From the results of our best-fitting model, we find that approximately half (i.e., $\pi_{\beta_1\gamma_1} + \pi_{\gamma_1} + \pi_{\beta_2\gamma_2} + \pi_{\gamma_2} + \pi_{\beta_1\gamma_2} + \pi_{\beta_2\gamma_1} = 0.50$) of the respondents used position, to some extent, as a schematic cue. Inspecting position probabilities (table 5) obtained from the position-specific constants for the best choices for LC3, we again see that irrespective of the item itself, respondents are systematically more inclined to choose an item if it is located at the top of the BWS task. This tendency reduces as the item approaches the bottom position. Startlingly, 40% of the respondents associated with the first set of position-specific constants (i.e., in the column denoted by $\Pr(s|\gamma_1)$) are predicted to choose the top item, no matter what it is. This proportion, however, drops to only 4% for the bottom position. While we add a cautionary note that this behavior only applies to a subset of 6% (i.e., $\hat{\pi}_{\gamma_1} = 0.06$ in LC3) of respondents, it is clearly non-trivial. Interestingly, the two sets of probabilities established for the worst positions show contrasting patterns. Respondents estimated as having $\hat{\gamma}_1$ appear to be subject to a strong centrality bias (Shaw et al. 2000; Attali and Bar-Hillel 2003), or center-stage effect (Valenzuela and Raghubir 2009), whereas a top-bottom effect (Meier and Robinson 2004; Dayan and Bar-Hillel 2011) is found for those with $\hat{\gamma}_2$. Taking the effects of item position on best and worst choices together, the results stemming from LC3 provide compelling evidence on the extent to which an institution's position influences its likelihood of being identified as the most and least trustworthy. This is an important finding and it provides important insight into the decision-making heuristics adopted in BWS.

In an attempt to uncover any differences in class membership due to individual characteristics, in table 6 we compare the mean conditional estimates of the LC3 class probabilities across different sociodemographic variables.[7] This reveals that, relatively speaking, male respondents are, on average, more than twice as likely to belong in the classes where $\hat{\gamma}_1$ is derived (i.e., $\bar{\pi}^*_{\beta_1\gamma_1} + \bar{\pi}^*_{\gamma_1} + \bar{\pi}^*_{\beta_2\gamma_1}$ totals 0.092 and 0.044 for males and females, respectively). While the respective aggregate conditional class membership probabilities associated with $\hat{\gamma}_2$ do not vary substantially between male and female respondents (0.445 and 0.425, respectively, obtained by $\bar{\pi}^*_{\beta_2\gamma_2} + \bar{\pi}^*_{\gamma_2} + \bar{\pi}^*_{\beta_1\gamma_2}$), we draw attention to the noticeably larger value of $\bar{\pi}^*_{\gamma_2}$ retrieved for male respondents. Collectively, the conditional class membership probabilities suggest that almost 30% of male respondents ($\bar{\pi}^*_{\gamma_1} + \bar{\pi}^*_{\gamma_2} = 0.287$) made their best and worst choices without regard to the items themselves, but rather used only the item's position to make their choices. In contrast, the relative proportion for female respondents is nearly half of that ($\bar{\pi}^*_{\gamma_1} + \bar{\pi}^*_{\gamma_2} = 0.163$). This gives a clear signal that male respondents appear more prone to infer position as a simplifying heuristic. Similarly, our results provide some evidence that the likelihood of position biases differed between age, level of education, employment, and, to a lesser extent, household income. Position bias aside, on average, respondents who are female, aged over 60, or are students all have a notably higher relative conditional probability of belonging in classes associated with $\hat{\beta}_1$ (i.e., $\bar{\pi}^*_{\beta_1}$, $\bar{\pi}^*_{\beta_1\gamma_1}$ and $\bar{\pi}^*_{\beta_1\gamma_2}$). In contrast,

[7] For this, we use Bayes' theorem to obtain a "posterior" estimate of the individual-specific class membership probabilities: $\pi^*_{cn} = \pi_c \prod_{t=1}^{T_n} \frac{\exp(V_{cnit})}{\sum_{j=1}^{J} \exp(V_{cnjt})} \Big/ \sum_{c=1}^{C} \pi_c \prod_{t=1}^{T_n} \frac{\exp(V_{cnit})}{\sum_{j=1}^{J} \exp(V_{cnjt})}$.

Table 6. Comparison of Conditional Estimates of the LC3 Class Probabilities across Individual Characteristics

	N	$\bar{\pi}^*_{\beta_1\gamma_1}$	$\bar{\pi}^*_{\beta_1}$	$\bar{\pi}^*_{\gamma_1}$	$\bar{\pi}^*_{\beta_2\gamma_2}$	$\bar{\pi}^*_{\beta_2}$	$\bar{\pi}^*_{\gamma_2}$	$\bar{\pi}^*_{\beta_1\gamma_2}$	$\bar{\pi}^*_{\beta_2\gamma_1}$
Gender									
Male	300	0.004	0.313	0.087	0.069	0.150	0.200	0.176	0.000
Female	316	0.011	0.405	0.032	0.055	0.126	0.131	0.239	0.000
Age									
18–45 years	377	0.010	0.372	0.087	0.042	0.094	0.178	0.217	0.000
46–60 years	131	0.003	0.281	0.012	0.103	0.240	0.193	0.168	0.000
Over 60 years	108	0.006	0.418	0.018	0.083	0.165	0.082	0.229	0.000
Educational attainment									
School level	335	0.008	0.346	0.069	0.056	0.119	0.191	0.211	0.000
Post-school qualification	281	0.008	0.377	0.047	0.070	0.159	0.133	0.206	0.000
Employment status									
Student	66	0.007	0.433	0.062	0.036	0.072	0.137	0.252	0.000
Employed	313	0.009	0.334	0.090	0.060	0.136	0.174	0.198	0.000
Unemployed/unable to work	141	0.009	0.357	0.020	0.065	0.145	0.199	0.203	0.000
Retired	96	0.004	0.402	0.013	0.082	0.176	0.104	0.220	0.000
Annual household income (gross)									
Less than £11,500	125	0.011	0.352	0.053	0.045	0.106	0.219	0.215	0.000
£11,500–£24,999	148	0.004	0.372	0.054	0.072	0.137	0.161	0.199	0.000
£25,000–£34,999	165	0.014	0.356	0.071	0.057	0.132	0.153	0.216	0.000
£45,000 and over	89	0.003	0.343	0.074	0.076	0.185	0.131	0.187	0.000
Undisclosed	89	0.004	0.378	0.038	0.064	0.146	0.149	0.221	0.000
Total	616	0.008	0.360	0.059	0.062	0.138	0.165	0.208	0.000

classes relating to $\hat{\beta}_2$ (i.e., $\bar{\pi}^*_{\beta_2}$, $\bar{\pi}^*_{\beta_2\gamma_1}$, and $\bar{\pi}^*_{\beta_2\gamma_1}$) appear to be relatively more likely to be comprised mostly of respondents who are male, aged between 46–60 years, retired, and whose annual household income falls in the highest category. These differences also suggest some observable sources of preference heterogeneity, as also revealed in Nilsson, Foster, and Lusk (2006) and Innes and Hobbs (2011).

Scenario Analysis

To further tease out the effects of position bias, we explore choice probabilities for a specific choice task. This analysis uses the estimates reported in table 3 to assess choice predictions under each of the model (and latent class) specifications. For this analysis, in order to clearly demonstrate the repercussions of the position bias, we deliberately place the items that were consistently found to be the least and most trustworthy, namely newspapers and the Food Standards Agency, at the top and bottom positions, respectively. For the intermediate positions, we place environmental groups, farmers/growers, and food industry scientists sequentially in positions 2–4 (as portrayed in figure 1). Results from this post-estimation analysis are given in table 7. For ease of comparison, we also report the expected values, which accounts for the unconditional class membership probabilities.

As expected, under the MNL model we observe the largest prediction for best choice to be the Food Standards Agency (51%), and newspapers having the smallest probability of choice (2%). The predictions for the worst choice are essentially the mirror image of the best choice (2% for FSA and 58% for newspapers).

Results arising from LC1 clearly show how the predictions differ depending on the processing strategy adopted by respondents. For respondents whose choices were in no way influenced by position, 70% are predicted to identify the Food Standards Agency as being the most trustworthy to provide accurate information on nanotechnology. This is in contrast to the prediction of only 14% who made their choices exclusively based on item position. Relatedly, whereas the respective prediction for newspapers is effectively zero in the first two latent classes, it jumps to 27% in the case of the third latent class, which is comprised of those who made choices based on item position only. Although there

Table 7. Scenario Probabilities

	Best					Worst				
	NewsPaps	EnvGrps	Farmers	FoodIndSci	FSA	NewsPaps	EnvGrps	Farmers	FoodIndSci	FSA
Model 1										
$\Pr(s)$	0.02***	0.12***	0.10***	0.25***	0.51***	0.58***	0.16***	0.16***	0.07***	0.02***
Model 2										
$\Pr(s\|\beta_1)$	0.00***	0.04***	0.04***	0.22*	0.70***	0.66***	0.16***	0.16***	0.02***	0.00***
$\Pr(s\|\beta_1,\gamma_1)$	0.01***	0.06***	0.04***	0.25*	0.65***	0.72***	0.12***	0.13***	0.03***	0.00***
$\Pr(s\|\gamma_1)$	0.27***	0.25***	0.18**	0.16***	0.14***	0.21	0.16***	0.18**	0.24***	0.22
$\mathbb{E}(\Pr(s))$	0.08***	0.10***	0.08***	0.21	0.54***	0.55***	0.15***	0.16***	0.08***	0.06***
Model 3										
$\Pr(s\|\beta_1,\gamma_1)$	0.00***	0.02***	0.03***	0.23	0.71***	0.67***	0.18	0.13***	0.02***	0.00***
$\Pr(s\|\beta_2,\gamma_2)$	0.11***	0.38***	0.20	0.13***	0.18	0.38***	0.08***	0.14***	0.26**	0.14***
$\mathbb{E}(\Pr(s))$	0.04***	0.14***	0.08***	0.20	0.53***	0.57***	0.15***	0.14***	0.10***	0.05***
Model 4										
$\Pr(s\|\beta_1)$	0.00***	0.01***	0.02***	0.26***	0.69***	0.65***	0.21	0.13***	0.01***	0.00***
$\Pr(s\|\beta_1,\gamma_1)$	0.02***	0.13	0.09**	0.30	0.46*	0.61***	0.18	0.19	0.02***	0.00***
$\Pr(s\|\gamma_1)$	0.40**	0.37***	0.14*	0.05***	0.04***	0.12**	0.12***	0.26*	0.35***	0.14
$\Pr(s\|\beta_2)$	0.02***	0.44***	0.08***	0.05***	0.41***	0.51***	0.02***	0.19	0.26*	0.03***
$\Pr(s\|\beta_2,\gamma_2)$	0.02***	0.50***	0.07***	0.05***	0.35**	0.57***	0.02***	0.13**	0.25	0.03***
$\Pr(s\|\gamma_2)$	0.24*	0.23*	0.18	0.19	0.16*	0.23*	0.17**	0.15***	0.21	0.24*
$\Pr(s\|\beta_1,\gamma_2)$	0.00***	0.02***	0.03***	0.29**	0.66***	0.74***	0.16	0.09***	0.01***	0.00***
$\Pr(s\|\beta_2,\gamma_1)$	0.05***	0.81***	0.06***	0.01***	0.07**	0.36**	0.01***	0.23	0.38***	0.02***
$\mathbb{E}(\Pr(s))$	0.07***	0.16*	0.07***	0.20	0.50***	0.54***	0.15***	0.14***	0.11***	0.05***

Note: The Krinsky-Robb (1986) simulation technique (using 100,000 draws) was employed to generate empirical distributions of the parameters, from which the standard errors were constructed (H_0: $\Pr(\cdot) = 0.2$ (i.e., 1/5); *p-value ≤ 0.05, **p-value ≤ 0.01 and ***p-value ≤ 0.001).

is, again, a reversal of the predictions as we move to the worst choice, position bias plays a somewhat lesser role.

The separate predictions based on LC2 are a consequence of differing levels of trust placed on the items and position-specific constants. For this model, we draw particular attention to the marked difference between predictions for the best and worst choices across the two classes, which is a consequence of different preferences as well as position effects.

Interpreting the predictions of LC1 and LC2 demonstrates the difficulty of deciphering whether these differences are an artifact of heterogeneous levels of trust or position bias. To some extent, LC3 overcomes this issue of confounding since both of these influences are isolated. For instance, comparing the two groups of respondents who made choices independently of position, we see that for one group the Food Standards Agency is deemed most trustworthy (i.e., $\Pr(s|\beta_1) = 0.69$), while for the other group it is environmental groups (i.e., $\Pr(s|\beta_2) = 0.44$). For both of these groups, the probability of choosing newspapers as being most trustworthy is effectively zero. However, as already established, for the respondents who completely disregarded the items and chose purely based on position, the probability of choosing newspapers as being most trustworthy is either approximately 40% or 24%, depending on which position-specific constants they are associated with (i.e., $\Pr(s|\gamma_1)$ or $\Pr(s|\gamma_2)$, respectively). Similarly, the item predicted as least trustworthy differs across the eight latent classes. Classes which retrieve only position-specific constants (i.e., $\Pr(s|\gamma_1)$ and $\Pr(s|\gamma_2)$, respectively), and thus accommodate position bias, predict a substantially larger share of respondents who select the Food Standards Agency as being the least trustworthy. Related to this, in both of these classes the respective predictions for newspapers are much reduced. We note here that the centrality bias identified in classes 1, 3, and 8 (i.e., $\Pr(s|\beta_1, \gamma_1)$, $\Pr(s|\gamma_1)$ and $\Pr(s|\beta_2, \gamma_1)$, respectively) has also led to relatively higher predictions of worst choices for farmers and food industry scientists.

Discussion and Conclusion

We present results from a best-worst scaling (BWS) study investigating consumers' trust in different sources of information regarding the use of nanotechnology in food production. As part of the analysis, we explore the behavioral proposition that respondents used position as a schematic cue when making choices in best-worst tasks. To empirically explore this issue, we use position-specific constants and a series of latent class logit models, where the classes differ according to: (1) the extent to which location confers a systematic advantage or disadvantage of being chosen, and/or (2) trust in institutions.

Hitherto, position effects have been overlooked in the analysis of BWS data. From this study, we report several important methodological insights. Firstly, a simple examination of observed choices and the use of a straightforward non-parametric test can help signal the extent of position effects in a given BWS dataset. However, using latent class logit models can further shed light on the issue. In our case study, we find that the choices made by around half of our sample were subject to a position effect. Furthermore, comparing the results from four different models, we consistently find evidence that the probability of an institution being chosen depends not only on the institution itself, but also on its position in the BWS choice task. In accordance with findings in the marketing and psychology literature, in all models we find that the institution positioned at the top of the choice task stands a significantly higher chance of having been identified as the most trustworthy. While we do find a position bias associated with the worst choice, it is not as strong compared to the best choice. We also find that the position effects differ between at least two subgroups of consumers. We further show that the socio-demographic characteristics of respondents differ across these subgroups. The most striking finding is that the choices made by male respondents were especially sensitive to a position bias.

From a modeling perspective, the consequences of overlooking position bias are clear. Substantial gains in model fit can be achieved and much richer insight into choice behavior and decision rules can be obtained. Failing to account for position bias can result in erroneous coefficients and ratio-scaled probabilities, and limit their validity when used for generating policy recommendations. Researchers engaged in the BWS method should be wary of this phenomenon. This should be especially considered at the experimental design stage, where it is possible to factor in that some respondents have an increased tendency to select the item positioned at the top when making their best choices, and, perhaps, the bottom item when they make their worst choices. Armed with this information, future studies should, at the very least, ensure that every effort is made to guarantee that the position of all items are rotated—so that each item appears an equal number of times in each vertical (or horizontal) dimension. The extent to which this randomization can help mitigate position bias would be a useful area for further research. However, it should be realized that this alone is unlikely to circumvent this issue, since, as we show—even where the item positions were fully balanced and randomized as part of the experimental design—a large proportion will make choices independently from the items themselves (irrespective of the order in which they are presented).

The number of items to include per best-worst task is another important consideration. While five items per BWS choice task has been found to be acceptable, we should be cognizant of the fact that this may have been a factor that led to respondents considering only a portion of the information available. With fewer items per task, there may be the potential to reduce these position effects.

Methodological aspects aside, we find, on average, that consumers tend to perceive information about nanotechnology and its use in food production to be most accurate and balanced when it originates from government institutions and scientists compared to non-government organizations, food handlers, friends and family, and the media. Our results reveal that consumers can be clearly segmented into at least two separate subgroups based on their trust perceptions. The first subgroup consists mainly of respondents who are female, aged over 60 years, and who are currently students and are more inclined to consider government institutions and scientists as trustworthy. The second subgroup predominately comprises respondents who are male, aged between 46–60 years, retired, and whose annual household income falls in the highest category. This group appears to consider non-government organizations, friends and family, and the media as being relatively more trustworthy. This insight provides valuable information for those who are engaged in communicating food safety. This is especially important as communication with consumers about emerging food safety concerns may help explain consumers' attitude towards accepting this new technology, which may then affect its adoption in the industry. Our results help ensure that communication can be achieved and contribute to more effective and successful awareness campaigns.

Some potential limitations of this study must be acknowledged. Firstly, while we wanted to bring position bias to the fore, we appreciate that there are a number of other decision-making heuristics and processing strategies that we did not address in this paper. This would be particularly important if one aims to explore meaningful differences among heuristics. Secondly, while our latent class segmentation of trust perceptions and position effects gives us a good understanding of the heterogeneity across respondents, we recognize that it would have been possible to further uncover within-class continuous variation and/or to increase the number of classes. We also note that socio-demographic variables could, of course, be included as covariates to help establish respondents' profiles. However, both of these would entail considerably more computational effort. Thirdly, for this analysis we do not implement nor compare our results against the models typically used in choice set generation analysis, such as the independent availability logit model (see Swait and Ben-Akiva 1987, and Swait 2001, for a description), which might be better-suited for retrieving which positions were taken into account by respondents. While initial effort was given in this area, with $J = 20$ best-worst pairs in our case, the choice set generation was too complex and computationally burdensome. We leave this challenge for further research, and suggest that it would be more feasible in case studies with fewer items per choice task. Fourthly, while we recognize the value of identifying the reasons explaining the adoption of these position effects, in this paper we focus only on the identification of such heuristics and how to accommodate them. Further, we focus only on position effects relating to the vertical dimension. An obvious extension to this paper would be to test whether or not similar results would be attained from BWS data based on horizontally arranged choice tasks.

Notwithstanding these potential limitations, our findings provide compelling evidence for further research in this area. We show the repercussions of failing to recognize position effects in the analysis of our BWS survey, which casts doubt on the appropriateness of previous BWS studies that have not addressed position bias. While the results of previous BWS studies should be viewed in this light, we must recognize that position effects may be unique to this dataset. We therefore encourage researchers who have already collected best-worst data to investigate whether their data shows such heuristics so that they can establish the prevalence of this phenomenon and gain a clearer understanding of its impact for policy recommendations. We provide a practical empirical solution for this prevalence, and our approach is applicable to datasets without supplementary questions, meaning that it can be employed in existing studies. Although we explore the issue of position bias in BWS, our approach can easily be adapted to explore other behavioral heuristics that may also be at play in BWS, as well as in other stated and revealed preference studies.

References

Attali, Y., and M. Bar-Hillel. 2003. Guess Where: The Position of Correct Answers in Multiple-choice Test Items as a Psychometric Variable. *Journal of Educational Measurement* 40 (2): 109–28.

Auger, P., T. Devinney, and J. Louviere. 2007. Using Best-worst Scaling Methodology to Investigate Consumer Ethical Beliefs across Countries. *Journal of Business Ethics* 70 (3): 299–326.

Baumgartner, H., and J.B.E. Steenkamp. 2001. Response Styles in Marketing Research: A Cross-National Investigation. *Journal of Marketing Research* 38 (2): 143–56.

Campbell, D., D.A. Hensher, and R. Scarpa. 2014. Bounding WTP distributions to Reflect the Actual Consideration Set. *Journal of Choice Modelling* 11 (1): 4–15.

———. 2012. Cost Thresholds, Cut-offs and Sensitivities in Stated Choice Analysis: Identification and Implications. *Resource and Energy Economics* 34 (3): 396–411.

Campbell, D., W.G. Hutchinson, and R. Scarpa. 2008. Incorporating Discontinuous Preferences into the Analysis of Discrete Choice Experiments. *Environmental and Resource Economics* 41 (3): 401–17.

Carlsson, F., M. Mørkbak, and S. Olsen. 2012. The First Time is the Hardest: A Test of Ordering Effects in Choice Experiments. *Journal of Choice Modelling* 5 (2): 19–37.

Chandon, P., J.W. Hutchinson, E.T. Bradlow, and S.H. Young. 2009. Does In-store Marketing Work? Effects of the Number and Position of Shelf Facings on Brand Attention and Evaluation at the Point of Purchase. *Journal of Marketing* 73 (6): 1–17.

Cohen, E. 2009. Applying Best-worst Scaling to Wine Marketing. *International Journal of Wine Business Research* 21 (1): 8–23.

Cohen, S., and B. Orme. 2004. What's your Preference? Asking Survey Respondents about Their Preferences Creates New Scaling Decisions. *Marketing Research* 16 (2): 32–7.

Day, B., I.J. Bateman, R.T. Carson, D. Dupont, J.J. Louviere, S. Morimoto, R. Scarpa, and P. Wang. 2012. Ordering Effects and Choice Set Awareness in Repeat-response Stated Preference Studies. *Journal of Environmental Economics and Management* 63 (1): 73–91.

Dayan, E., and M. Bar-Hillel. 2011. Nudge to Nobesity II: Menu Positions Influence Food Orders. Discussion paper series, The Center for the Study of Rationality, Hebrew University, Jerusalem.

Doornik, J.A. 2009. *An Object-oriented Matrix Programming Language Ox 6*. London: Timberlake Consultants Ltd.

Erdem, S., D. Campbell, and A.R. Hole. 2014. Accounting for Attribute-level Non-attendance in a Health Choice Experiment: Does it Matter? *Health Economics*. doi: 10.1002/hec.3059.

Erdem, S., D. Campbell, and C. Thompson. 2014. Elimination and Selection by Aspects in Health Choice Experiments: Prioritisation Health Service Innovations. *Journal of Health Economics* 38 (1): 10–22.

Erdem, S., and D. Rigby. 2013. Investigating Heterogeneity in the Characterization of Risks Using Best-Worst Scaling. *Risk Analysis* 33 (9): 1728–48.

Erdem, S., D. Rigby, and A. Wossink. 2012. Using Best-worst Scaling to Explore Perceptions of Relative Responsibility for Ensuring Food Safety. *Food Policy* 37 (6): 661–70.

Finn, A., and J. Louviere. 1992. Determining the Appropriate Response to Evidence of Public Concern: The Case of Food Safety. *Journal of Public Policy & Marketing* 11 (1): 12–25.

Flynn, T.N., J.J. Louviere, T.J. Peters, and J. Coast. 2007. Best-Worst Scaling: What it Can do for Health Care Research and How to do it. *Journal of Health Economics* 26 (1): 171–89.

Guney, B. 2014. A Theory of Iterative Choice in Lists. *Journal of Mathematical Economics* 53 (1): 26–32.

Hensher, D.A., A.T. Collins, and W.H. Greene. 2012. Accounting for Attribute Non-Attendance and Common-Metric Aggregation in a Probabilistic Decision Process Mixed Multinomial Logit Model: a Warning on Potential Confounding. *Transportation* 40 (5): 1003–20.

Hensher, D.A., J.M. Rose, and W.H. Greene. 2005. The Implications on Willingness to Pay of Respondents Ignoring Specific Attributes. *Transportation* 32 (3): 203–22.

Hess, S., A. Stathopoulos, D. Campbell, V. O'Neill, and S. Caussade. 2012. It's Not That I Don't Care, I Just Don't Care Very Much: Confounding Between Attribute Non-attendance and Taste Heterogeneity. *Transportation* 40 (3): 583–607.

Inman, J.J., L. McAlister, and W.D. Hoyer. 1990. Promotion Signal: Proxy for a Price Cut? *Journal of Consumer Research* 17 (1): 74–81.

Innes, B.G., and J.E. Hobbs. 2011. Does It Matter Who Verifies Production-Derived Quality? *Canadian Journal of Agricultural Economics* 59 (1): 87–107.

Koppell, J.G., and J.A. Steen. 2004. The Effects of Ballot Position on Election Outcomes. *The Journal of Politics* 66 (1): 267–81.

Krinsky, I., and A.L. Robb. 1986. On Approximating the Statistical Properties of Elasticities. *The Review of Economics and Statistics* 68 (4): 715–19.

Louviere, J.J. 1993. The Best-worst or Maximum Difference Measurement Model: Applications to Behavioral Research in Marketing. Paper presented at the American Marketing Association's Behavioral Research Conference, Phoenix, AZ.

Louviere, J.J., and T.N. Flynn. 2011. Using Best-worst Scaling Choice Experiments to Measure Public Perceptions and Preferences for Healthcare Reform in Australia. *The Patient: Patient-Centered Outcomes Research* 3 (4): 275–83.

Lusk, J.L., and B.C. Briggeman. 2009. Food Values. *American Journal of Agricultural Economics* 91 (1): 184–96.

Manski, C.F. 1977. The Structure of Random Utility Models. *Theory and Decision* 8 (3): 229–54.

Marley, A.A.J., and J.J. Louviere. 2005. Some Probabilistic Models of Best, Worst, and Best-Worst Choices. *Journal of Mathematical Psychology* 49 (6): 464–80.

McArthur, L., and D. Post. 1977. Figural Emphasis and Person Perception. *Journal of Experimental Social Psychology* 13 (6): 520–35.

Meier, B., D. Hauser, M. Robinson, C. Friesen, and K. Schjeldahl. 2007. What's Up With God? Vertical Space as a Representation of the Divine. *Journal of Personality and Social Psychology* 93 (5): 699–710.

Meier, B.P., and M.D. Robinson. 2004. Why the Sunny Side Is Up: Associations Between Affect and Vertical Position. *Psychological Science* 15 (4): 243–47.

Mørkbak, M., S. Olsen, and D. Campbell. 2014. Behavioral Implications of Providing Real Incentives in Stated Choice Experiments. *Journal of Economic Psychology* 45 (1): 102–16.

Nilsson, T., K. Foster, and J.L. Lusk. 2006. Marketing Opportunities for Certified Pork Chops. *Canadian Journal of Agricultural Economics* 54 (4): 567–83.

Nisbett, R.E., and T.D. Wilson. 1977. Telling More Than We Can Know: Verbal Reports on Mental Processes. *Psychological Review* 84 (3): 231–59.

Raghubir, P., and A. Valenzuela. 2006. Center-of-Inattention: Position Biases in Decision-Making. *Organizational Behavior and Human Decision Processes* 99 (1): 66–80.

Rodway, P., A. Schepman, and J. Lambert. 2013. The Influence of Position and Context on Facial Attractiveness. *Acta Psychologica* 144 (3): 522–29.

Rozin, P., S. Scott, M. Dingley, J.K. Urbanek, H. Jiang, and M. Kaltenbach. 2011. Nudge to Nobesity I: Minor Changes in Accessibility Decrease Food Intake. *Judgment and Decision Making* 6 (4): 323–32.

Rubinstein, A., A. Tversky, and D. Heller. 1997. Naive Strategies in Competitive Games. In *Understanding Strategic Interaction: Essays in Honor of Reinhard Selten*.

eds. W. Albers, W. Güth, P. Hammerstein, B. Moldovanu and E. van Damme, 394–402. Berlin: Springer-Verlag Berlin Heidelberg.

Scarpa, R., T.J. Gilbride, D. Campbell, and D.A. Hensher. 2009. Modelling Attribute Non-Attendance in Choice Experiments for Rural Landscape Valuation. *European Review of Agricultural Economics* 36 (2): 151–74.

Scarpa, R., S. Notaro, J. Louviere, and R. Raffaelli. 2011. Exploring Scale Effects of Best/Worst Rank Ordered Choice Data to Estimate Benefits of Tourism in Alpine Grazing Commons. *American Journal of Agricultural Economics* 93 (3): 813–28.

Scarpa, R., R. Zanoli, V. Bruschi, and S. Naspetti. 2013. Inferred and Stated Attribute Non-Attendance in Food Choice Experiments. *American Journal of Agricultural Economics* 95 (1): 165–80.

Schubert, T. 2005. Your Highness: Vertical Positions as Perceptual Symbols of Power. *Journal of Personality and Social Psychology* 89 (1): 1–21.

Shaw, J.I., J.E. Bergen, C.A. Brown, and M.E. Gallagher. 2000. Centrality Preferences in Choices Among Similar Options. *The Journal of General Psychology* 127 (2): 157–64.

Swait, J. 2001. A Non-Compensatory Choice Model Incorporating Attribute Cut-Offs. *Transportation Research Part B: Methodological* 35 (10): 903–28.

Swait, J., and M. Ben-Akiva. 1987. Incorporating Random Constraints in Discrete Models of Choice set Generation. *Transportation Research Part B: Methodological* 21 (2): 91–102.

Thurstone, L.L. 1927. A Law of Comparative Judgment. *Psychological Review* 34 (4): 273–86.

Valenzuela, A., and P. Raghubir. 2010. Are Consumers Aware of Top-Bottom but Not of Left-Right Inferences? Implications for Shelf Space Positions. Working Paper, Baruch College, City University of New York.

———. 2009. Position-Based Beliefs: The Center-Stage Effect. *Journal of Consumer Psychology* 19 (2): 185–96.

Valenzuela, A., P. Raghubir, and C. Mitakakis. 2013. Shelf Space Schemas: Myth or Reality? *Journal of Business Research* 66 (7): 881–8.

van Kleef, E., K. Otten, and H.C. van Trijp. 2012. Healthy Snacks at the checkout counter: A Lab and Field Study on the Impact of Shelf Arrangement and Assortment Structure on Consumer Choices. *BMC Public Health* 12 (1):1072.

Wright, P. 2002. Marketplace Metacognition and Social Intelligence. *Journal of Consumer Research* 28 (4): 677–82.