Joint use of attribute importance rankings and non-attendance data in choice experiments

Article

Accepted Version

Chalak, A., Abiad, A. and Balcombe, K. (2016) Joint use of attribute importance rankings and non-attendance data in choice experiments. European Review of Agricultural Economics, 43 (5). pp. 737-760. ISSN 0165-1587 doi: 10.1093/erae/jbw004 Available at https://centaur.reading.ac.uk/56694/

To link to this article DOI: http://dx.doi.org/10.1093/erae/jbw004

Publisher: Oxford University Press

Joint Use of Attribute Importance Rankings and Non-attendance Data in Choice Experiments

Ali Chalak [a,1], Mohamad Abiad [b] and Kelvin Balcombe [c]

[a] *Department of Agriculture, Faculty of Agricultural and Food Sciences, American University of Beirut, P.O. Box 11-0236 Riad el Solh, Beirut 1107-2020, Lebanon*

[b] *Department of Nutrition and Food Science, Faculty of Agricultural and Food Sciences, American University of Beirut, P.O. Box 11-0236 Riad el Solh, Beirut 1107-2020, Lebanon*

[c] *Department of Food Economics and Marketing, School of Agriculture Policy and Development, University of Reading, Earley Gate, P.O. Box 237, Reading RG6 6AR, United Kingdom*

[1] Corresponding author. Tel.: +961-1-350000 ext. 4502. Fax: +961-1-744460. Email address: ac22@aub.edu.lb.

Joint Use of Attribute Importance Rankings and Non-attendance Data in Choice Experiments

Abstract

The joint and alternative uses of attribute non-attendance and importance ranking data within discrete choice experiments are investigated using data from Lebanon examining consumers' preferences for safety certification in food. We find that both types of information; attribute non-attendance and importance rankings, improve estimates of respondent utility. We introduce a method of integrating both types of information simultaneously and find that this outperforms models where either importance ranking or non-attendance data are used alone. As in previous studies, stated non-attendance of attributes was not found to be consistent with respondents having zero marginal utility for those attributes.

Key words: attribute importance ranking; attribute non-attendance; Bayesian; choice experiment; mixed logit

1. Introduction

There has been growing interest in recent years in the use of answers to debriefing questions to further refine the estimates of preference parameters from discrete choice models. These developments have followed from the field of enquiry examining information processing strategies invoked by respondents to solve choice tasks. Particular interest has been given to what has been termed attribute non-attendance (ANA). In the case of ANA, respondents would decide to ignore, or assign low importance to, a subset of attributes. Following studies by Hensher and colleagues (Hensher, et al., 2007; Hensher, et al., 2005), ANA has since been extensively investigated within the fields of transportation economics (Collins, et al., 2013; Hensher & Rose, 2009; Hensher, et al., 2012; Hess & Hensher, 2010, 2013; Hess, et al., 2013), health economics (Hole, 2011; Lagarde, 2013) environmental economics (Alemu, et al., 2013; Campbell, et al., 2011a; Campbell, et al., 2011b; Kragt, 2013; Scarpa, et al., 2009) and agricultural economics (Balcombe, et al., 2014; Balcombe, et al., 2011; Balcombe, et al., 2015b; Colombo & Glenk, 2013; Kehlbacher, et al., 2013; Scarpa, et al., 2013).

This ANA literature has followed two threads of inquiry. One has sought to establish whether ANA exists, since it may be symptomatic of non-compensatory behaviour on behalf of respondents which threatens the validity of choice experiments. The other thread has sought to use ANA as an additional source of information about respondents' preferences. Two main approaches have been used to elicit ANA: stated and inferred. In inferred ANA, suitable econometric models are used to determine the possibility that an attribute or combination of attributes are being ignored such that their marginal utilities become equal to zero (Campbell, et al., 2011b; Hensher & Greene, 2010; Hensher, et al., 2012; Hole, 2011; Lagarde, 2013; Scarpa, et al., 2009). Stated ANA uses the information from supplementary questions following choice tasks and asking respondents whether they paid attention to each of the attributes. This information is then used to condition parameters such that they account for ANA. At the extreme this can involve simply setting the marginal utilities for some attributes to zero (Colombo & Glenk, 2013; Hensher, et al., 2005; Hensher & Rose, 2009) or otherwise reducing their magnitudes by means of either covariates or scaling factors (Alemu, et al., 2013; Balcombe, et al., 2014; Balcombe, et al., 2011; Hensher, et al., 2007; Hess & Hensher, 2010; Kehlbacher, et al., 2013).

There is a view that inferred ANA is a better way to identify 'true ANA' compared to stated ANA (Hensher, et al., 2012; Hess & Hensher, 2013; Kragt, 2013). This is because the majority of studies conclude that respondents' stated ANA may not signify zero marginal utilities. Therefore, some consensus has emerged that it is probably incorrect to adopt a practice of assigning zero marginal utility to respondents stating ANA for given attributes. However, it remains an open question as to whether and how stated ANA responses should be used to infer something about the nature of preferences. Also, it has been suggested that information from various ANA statements should be employed rather than utilizing only one (Alemu, et al., 2013; Hess & Hensher, 2010, 2013). Concerns have been expressed about potential endogeneity problems and the confounding between ANA and attribute heterogeneity (Collins, et al., 2013; Hensher, et al., 2013; Hess, et al., 2013). Two principal avenues are open for the integration of stated ANA into the estimation. The first is the 'direct' use of ANA data within the likelihood functions which characterise choice, and the second is the latent variable approach (Hess & Hensher, 2013). The second has been partly motivated by a desire to mitigate or avoid 'endogeneity issues'. Yet existing latent approaches have been based on independence of the latents with additive Gumbel-distributed errors. Also, if one posits a latent variable structure then simply replacing a latent variable with an observable implies misspecification (and in a sense endogeneity). On the other hand, the direct use of measures can alternatively be thought of as a reduced form, emanating from an unspecified latent structure. It is this view that is adopted here. This said, with the acceptance that stated ANA may be informative about the nature of preferences, the immediate question which follows is whether other forms of debriefing questions such as attribute rankings can be used as an alternative to, or in conjunction with, stated ANA.

This paper investigates using two different statements from respondents regarding attributes' non-attendance and importance rankings and combined in a fashion similar to Balcombe, et al. (2015b). The first is a yes/no type of ANA question. The second asks respondents to rank attributes in order of importance to their choice. Moreover, rather than assigning zero values to the marginal utilities of ignored attributes, we use a 'contraction' approach (Balcombe, et al., 2015b; Kehlbacher, et al., 2013) to account for the effect of ANA on the magnitudes of marginal utilities. Econometrically, we employ a Bayesian mixed logit framework for data estimation similar to the one found in Scarpa, et al. (2009) and Balcombe, et al. (2011). In previous applications, Balcombe, et al. (2014) introduced an approach that investigates the usefulness of ranking measures alone. Balcombe, et al. (2015b) examined the integration of ANA and visual attention measures. The ANA and ranking approaches were compared separately in Balcombe, et al. (2015a). This is the first paper to use both ANA and ranking measures jointly as opposed to using them as substitutes. The approach herein would account for the fact that both measures (ranking and ANA) may not be known precisely, and the elicitation and inclusion of both may improve the model.

ANA and ranking data potentially contain information that in a sense are non-overlapping. Importantly, most respondents do not seem to have a problem in ranking attributes, even when they have indicated non-attendance to multiple attributes. In this case one might imagine respondents experiencing difficulties since non-attended options may seem equally unimportant. However, this generally seems not to be the case since all respondents were able to complete the ranking task, even if they had not attended multiple attributes. This seems to concord with the preceding literature; for example, in eye-tracking studies, the fixation duration, taken to be a measure of attention accorded to attributes, tends to be the same between stated attenders and non-attenders (Balcombe, et al., 2015b). This in itself is perhaps further evidence that when respondents state non-attendance, they have actually considered these attributes when completing choice tasks. If this is the case then it is possible that the ranking of attributes supersedes ANA data. However, this need not be the case because stated ANA may still provide a discrete indication of a substantive shift in the importance of attributes that is not measured by ranking. Indeed what has also been established in the literature is that those who state that they ignore attributes tend to be less sensitive to these attributes than average.

This paper is structured as follows: in the next section we describe the choice experiment, survey design, sampling and data collection. We then formally introduce the model structure and how we use the ANA and ranking data. We then employ these to analyse the data and present the results in the next section. The last section concludes.

2. Materials and methods

2.1 Application – Consumer preferences for food safety under various certifying regimes in Lebanon

Our specific application is a discrete choice experiment (DCE) that investigates the influence of various safety certification schemes on consumers' preferences for a traditional snack that is widely consumed in Beirut, Lebanon. In the past 5 years, food safety has been at the forefront of public debate in this Middle Eastern developing country following a series of highly publicised food scares, the most recent of which triggered by statements by the Minister of Public Health deploring the dire microbiological safety and hygiene conditions at work throughout the agri-food chain (The Daily Star, 2014).

Food safety is a major public health concern around the globe, with foodborne diseases and illnesses causing millions of people to be hospitalized every year, often leading to death (Notermans, et al., 1995; Redmond & Griffith, 2004; WHO, 2011). In developing countries, the situation is very often aggravated by the under-reporting of foodborne illnesses and diseases and the limited, if any, public authority or ministerial oversight and control over food handling practices and hygiene. Though consumers' knowledge and awareness of proper food handling practices may be minimal, putting them at higher risks of contracting foodborne illnesses, evidence suggests that they highly value safer food and state high willingness to pay (WTP) for third-party safety certification schemes (Angulo & Gil, 2007; Baker, 1999; Chalak & Abiad, 2012; Enneking, 2004) and quantitative reductions in risks of foodborne illness (Goldberg & Roosen, 2007; Teisl & Roe, 2010).

Yet if such schemes are to be fully valorised in the market, it is essential to optimize the information they provide, be it in the form of awareness campaigns, advertising, or labelling, in order to maximize consumer surplus extraction. Therefore a more in-depth understanding of the potential influences of information provision on consumers' food purchasing decisions becomes of paramount importance. In the MENA region, Chalak and Abiad (2012) and Abiad and Chalak (2012) have investigated consumers' preferences for various third-party safety certification schemes, such as ISO 22000 and ServSafe® in Lebanon, and found a significant WTP for their provision for a highly popular street food. Though safety certification is not unheard of in the region, it remains limited in its market scope to a small group of food establishments catering almost exclusively for safety-conscious middle- and upper-class consumers. This application builds on these studies to examine consumers' preferences for various policy settings under which such certification schemes could be provided, and also investigates the interplay between the various ‘qualitative' food safety certification schemes under study, and the ‘quantitative' foodborne risk reductions effected by each of them. This application provides some insights into consumers' perceptions, attitudes and judgments as to what type of certification scheme guarantees food safety and to what extent. Though a full development of these insights will be undertaken in a separate policy-oriented paper, we will present some preliminary findings herein.

A choice experiment (CE) was designed to study the influence of various safety certification schemes, including the local, the internationally-recognized and the governmental, on consumers' choice of shawarma sandwiches. In the absence of real market data, choice experiments can be useful in understanding consumers' purchasing behaviour as it closely simulates market choice situations. When carefully designed, CEs can yield credible estimates of willingness to pay (WTP) and market share gains for new products, new features in existing products, or changes in the level of provision of one or more attributes of existing products. This has made CEs and related stated preference methods a tool of choice among many marketing researchers and practitioners since the 1960s (Louviere, et al., 2000, p. 283).

CEs are part of a wider set of stated preference methods known as attribute-based methods (ABMs). In the context of food choice, ABMs present survey respondents with a number of meal or portion attributes (e.g., portion size, safety certification, location) that can be provided at different possible levels. In addition, the costs of the various proposed changes to product attributes are usually proposed by means of changes of a price attribute. Consumers are asked to choose their most preferred product from a set of options differing in terms of their attribute levels as described in choice cards or sets presented to them. Repeated choices by consumers from a set number of choice cards reveals the trade-offs customers are willing to make between the attributes (Hanley, et al., 2001). From the resulting choice data, the preference parameters of the various attributes of the good can then be estimated using appropriate econometric tools, as will be detailed in the next section.

2.2 Survey design

The survey design was informed by the findings from a focus group conducted for a similar food safety study that we conducted in 2011 (Abiad & Chalak, 2012; Chalak & Abiad, 2012), and upon which the current study builds. Both studies were based on food safety certification as it shapes shawarma (a Levantine Arab beef, lamb or chicken-based meat preparation similar to the Turkish *doner kebab* and Greek *gyros*) purchasing decisions and both shared the same non-safety attributes. The emphasis of the focus groups was mainly on non-sensory aspects. Though sensory attributes (e.g. taste) were also discussed, it turned out that location/convenience of the food shop or order, the size of the portion and of course price were the most important non-sensory attributes to consumers and subsequently were included alongside the food safety attributes of interest in this survey design similarly to the previous study.

This choice of attributes was broadly justified by the empirical literature on non-sensory determinants of food choice which was reviewed by Jaeger (2006). Among the factors enumerated, convenience as reduction of the time and effort in the meal process is deemed important. Also, price is discussed in its capacity both as an aspect of food to be traded against various qualities of the food product, and as a perceived indicator of quality in itself. Personal health is also considered important, and though the focus is on dietary habits and nutritional value, personal health could also be extended to encompass food safety. Branding is seen as the main motor of business profits, as it plays various important roles for the consumer, among which feature risk reduction as a sign of quality. Indeed food safety certificates, often made visible by means of widely recognized labels, could be considered to be a means of achieving brand value.

In order to gauge the additional effect of quantitative risk reduction on the valuation of food safety certification, we adopted a split-sample approach. In this design, choice tasks that were otherwise identical differed in their inclusion, or not, of a quantitative risk reduction attribute alongside the various safety certificates which goal is to effect them. In the first ‘without risk attribute’ information treatment, the food safety information presented to respondents was only embodied in the safety certification attributes that ranges from the locally offered to the internationally recognized safety certificates. In the second ‘with risk attribute’ information treatment, respondents also received information on the percent reduction in risk of foodborne illness in the safety-certified sandwiches compared to the uncertified sandwiches.

As mentioned above, this design ultimately helps understand the interplay between the various 'qualitative' food safety certification schemes under study, as well as the 'quantitative' foodborne risk reductions effected by each of them. Insights from such an analysis would help optimize the food safety information embedded by food safety certificates, be it qualitative or quantitative, in a way to maximize consumer surplus extraction. The split-sample design also allows establishing 'value-added thresholds' of quantitative safety risk reductions for each certification scheme. That is, using this design, one can determine which minimum level of risk reduction needs to be met by the safety certificate for advertising it, alongside the 'qualitative' message borne by the safety label, to become cost-beneficial. Yet it is not our aim to discuss the full implications of these results in this paper, and we leave their development for another policy-oriented paper.

The final list of attributes is shown in Table 1. The certification attribute described the safety certificate, if any, obtained by the hypothetical vendor serving shawarma, with a focus on the type of certifying body and with all the implications this would have on the degree of rigor in enforcement and monitoring. These bodies varied from (i) local third-party certifying bodies that would provide safety inspection and training services tailored to the needs of the food service, to the (ii) internationally recognized certificates, such as ISO22000, that are more thorough and more directed to food industry establishments, to a (iii) hypothetical Ministry of Public Health (MoPH) safety certification scheme that goes beyond mere licensing of food establishments to their regular and mandatory inspection and monitoring[2]. In addition to certification, the 'percent reduction in risk of foodborne illness' attribute features in choice tasks presented only to a 'with risk attribute' sub-sample. The reductions in risk accompanying each certificate were expressed as percentages which ranges varied with the type of certification; third-party local bodies being considered less rigorous than either internationally-recognized or MoPH. Both the certification and risk reduction attributes were developed by consulting a food safety and microbiology expert and faculty member at the American University of Beirut (Dr. Zeina Kassaify, personal communication, February 12, 2012).

[2] Currently, the Ministry of Public Health (MoPH) is the governmental body in charge of ensuring the safety of food establishments in Lebanon. Yet its efforts to guarantee food safety do not go beyond mere licensing at the time of the establishment of the business. In our choice experiment, we ask respondent to imagine a case in which the MoPH would upgrade its services to include, in addition to licensing, mandatory and regular safety and hygiene inspections of food service establishments that would comply with the same internationally-recognized standards observed by certification schemes like ISO22000.

Table 1. Attributes and attribute levels used in the choice experiment

Attribute	Levels	Description of levels	
Certification	4	1. No certification 2. Third-party local 3. Internationally-recognized 4. Upgraded MoPH	
Location and convenience	4	1. Round the corner (less than 5-minute walk) 2. Within walking distance (more than 5-minute walk) 3. Need to go there by car 4. Delivery order	
Portion size	2	1. Typical small-sized sandwich (approx. 15 cm) 2. Medium-sized sandwich (approx. 25 cm)	
Change in risk of foodborne illness (only in the ‘with risk attribute’ information treatment)	4	No certification	1. 0% No change
		Third-party local	1. 0% No change 2. 20% Reduction 3. 35% Reduction 4. 70% Reduction
		Internationally-recognized / Upgraded MoPH	1. 35% No change 2. 70% Reduction 3. 90% Reduction 4. 99% Reduction
Price increase	6	1. LBP0 2. LBP500 3. LBP1,500 4. LBP2,500 5. LBP4,000 6. LBP6,000	

The location/convenience attribute described the distance to the food shop serving the shawarma product or the way the product is ordered; that is, whether the shop offering the shawarma product is around the corner, within a walking distance of more than ten minutes or accessible by car, or whether the product could be ordered by delivery. The portion size attribute contrasted the typically served small-sized sandwiches (approximately 15cm long) to the medium-sized sandwiches that are commonly encountered in many food shops serving shawarma (approximately 25cm long). Finally, price increase ranged from LBP0 to LBP6,000 (USD3.96)[3] *above the price* that each respondent usually pays for his sandwich of shawarma. In comparison, more than 90% of consumers in Greater Beirut typically pay between LBP2,500 (USD1.65) and LBP5,000 (USD3.30) for a small-sized shawarma sandwich, with an average price of LBP3,980 (USD2.63), and therefore we have provided for the possibility that some consumers could pay considerably high premiums for safer, closer or more convenient, and/or medium-sized shawarma products; indeed a third of the sandwiches are offered at premiums of LBP4,000 or LBP6,000, hence at least double the price of their uncertified counterparts.

Respondents were presented with a series of choice sets each including four hypothetical shawarma products or options described in terms of their attributes (which included the risk reduction attribute, depending on whether the respondents was randomly allocated to the 'with risk attribute' treatment). The CE is a labelled CE in that each choice task had all three types of certificates in addition to no certification, whereby the first, second, third and fourth options would have no safety, local third-party, internationally-recognized, and upgraded MoPH certificates, respectively. In addition, an opt-out option ('none of these') was included to avoid forcing respondents to make choices. Last, we included a 'cheap talk' script right before the choice tasks to describe the propensity of respondents to inflate their stated WTPs in this type of surveys. Both opt-out options and cheap-talk scripts have been advocated in the stated preference literature as tools to help reduce the problem of hypothetical bias and align stated WTP with 'true' WTP (Hensher, 2010).

[3] LBP stands for Lebanese pound. USD1 = LBP1,515.

Figure 1. Example of a choice set

CHOICE CARD 3

	Option 1	Option 2	Option 3	Option 4	
Certification	No certification	Third-party local	Internationally-recognized	Upgraded MoPH	None of these
Location and Convenience	Within walking distance (more than 5-minute walk)	Within walking distance (more than 5-minute walk)	Need to go there by car	Around the corner (less than 5-minute walk)	
Portion Size	Medium-sized sandwich (approx. 25cm)	Typical small-sized sandwich (approx. 15 cm)	Typical small-sized sandwich (approx. 15 cm)	Typical small-sized sandwich (approx. 15 cm)	
Change in risk of foodborne illness	0% No change	35% Reduction	90% Reduction	70% Reduction	
Price Increase	LBP 2,500	LBP 6,000	LBP 4,000	LBP 0	
Please choose the ONE option you prefer most	☐	☐	☐	☐	☐

The choices that respondents stated in each choice set were the result of trade-offs between attribute and price levels which are systematically varied across options and choice sets. Respondents then had to state which product they would purchase if they had the choice in a real market situation. An example of a choice set used in this study is shown in Figure 1. An experimental design with a Bayesian information structure maximizing a D_b-optimal criterion was employed to generate twelve choice sets that were presented to each respondent (Ferrini & Scarpa, 2007). Information from a pilot survey with a main-effects fractional factorial design, conducted earlier with 50 students from the American University of Beirut, Lebanon, were used to optimize the design parameters of the main stage survey[4].

[4] The pilot was conducted using the 'with risk attribute' treatment, and constrained the level of foodborne risk reduction level to 0% for the 'No certification' option while allowing it to vary freely for the 'Third-party local', 'Internationally-recognized' and 'Upgraded MoPH' options. The design was obtained after 25,000 iterations with 500 Halton draws per iteration, achieving a D_b-error of 0.0698. To align the 'without risk attribute' with the 'with risk attribute' questionnaires and minimize differences between the two, the experimental design of the 'without risk attribute' treatment was generated by simply dropping the risk reduction attribute from the choice sets. We recognize that developing a *D*-optimal design for the 'with risk attribute' treatment and then removing an attribute from the 'without risk attribute' treatment means that the latter design is no longer necessarily *D*-optimal. However, subject to the constrained model being a valid specification, this means that while the efficiency of the results may be less, the results should be consistent. The advantage of not redesigning the choice sets to have two different optimal designs is

The survey questionnaire was composed of three sections. The first included a wide range of background questions covering food safety habits, attitudes, perceptions and knowledge as well as food purchasing behaviour. The second section consisted of the core choice exercise which was centred on the twelve choice sets generated by the D_b-optimal design followed by a set of debriefing questions that included a non-attendance and importance ranking question for each attribute. Finally, the third and last section collected sociodemographic data on both respondents and their households.

The attribute attendance question asked respondents the following: "Thinking about all the different attributes of the shawarma sandwich, indicate for each whether or not you have taken it into consideration while making your choices". In addition to 'Yes' and 'No' options, respondents were also given the option of answering 'Don't know'. As for the wording of the attribute ranking questions, it was as follows: "Thinking about all the different attributes of the shawarma sandwich, how would you rank each of the following in terms of importance during your decision making", and they were further instructed that "ranks range from 1 (most important) to 5 (least important)". Needless to say, care was taken by the interviewers to ensure that respondents state an answer for each attribute in the attendance question, and consistently rank all attributes in the ranking question.

2.3 Household interviews

The main stage survey covered Greater Beirut, an area comprising central administrative Beirut; the political and economic capital of Lebanon, and its suburbs located in various contiguous districts of the Mount-Lebanon governorate. This study was approved by the American University Institution Review Board (IRB). In order to ensure the anonymity of the respondents, no personal identifiers (e.g., names, addresses, and phone numbers) were collected. The study was completely voluntary, and participants were given the choice to quit at any time and refrain from answering any question(s). A representative sample of 700 respondents aged 18 to 64 of the Greater Beirut households at large was selected for face-to-face home interviews between May 23rd and June 11th, 2012.

---

that we can be sure that any differences between the 'with' and 'without risk attribute' results can be directly ascribed to the removal of the attribute, and not any other change in design properties.

A multi-stage probability sampling was adopted to ensure a random, geographically representative sample for identifying households and main respondents. Greater Beirut is composed of several areas, namely the sectors that make up Central Administrative Beirut in addition to suburban areas that are located in four adjacent districts. Questionnaires were distributed proportionately to the number of registered voters in the areas to be covered. In a first stage, neighbourhoods inside each area were selected in a way to represent the make-up of these areas, while in a second stage, households were selected in each neighbourhood based on a systematic random sample that is proportional to the number of buildings within it. Finally, in a third stage, a primary respondent was sampled within each household based on the most recent birthday. Those who reported never having purchased shawarma sandwiches for varying reasons (e.g., being vegetarian, not liking shawarma etc.) were excluded from the analysis (n=103). Hence the final sample size for analysis included 597 respondents: 293 in the 'without risk attribute' and 304 in the 'with risk attribute' treatments.

Characteristics of the treatment sub-samples as well as the Greater Beirut population are presented in Table 2. In terms of gender, both our sub-samples slightly over-represent males and under-represent females, such that the gender split is significantly different from that reported in the 2007 household survey for the Greater Beirut population (MoSA, et al., 2008). The feedback from fieldworkers was that in some cases, female household members preferred not to conduct the interview out of cultural or religious conservatism, hence biasing the sample composition. As for the age split, our sample significantly under-represents younger age groups (18 to 24 years old) and over-represents older age groups compared to the 2007 household survey figures for Greater Beirut, while individuals aged 25 to 39 are adequately represented. This is at least partly due to the fact the 2007 household survey aggregates age categories differently from our sample, such that it was not possible to separate Greater Beirut residents aged 15 to 17 from those aged 18 to 24, hence inflating the ranks of this category and deflating those of the others, notably the oldest (40 to 64 years old). Finally, the 2007 household survey did not report household income figures so we compared the average sub-sample incomes to the ones reported in the 2004 household survey ((MoSA, et al., 2006)). In both cases the differences are insignificantly different from the target population.

Table 2. Sociodemographic characteristics of the treatment sub-samples and the Greater Beirut population (where available)

Characteristic	Without risk attribute (n=293)	With risk attribute (n=304)	Greater Beirut
Gender			
Male	**55.97%** *	**53.62%**	48.39%
Female	**44.03%**	**46.38%**	51.61%
Age			
18 - 24 years	**19.80%**	**21.71%**	29.31%
25 - 39 years	34.13%	35.20%	35.44%
40 - 64 years	**46.08%**	**43.09%**	35.25%
Education			
Elementary (Less than high school degree)	20.14%	18.42%	-
Secondary/High school (12 years of schooling)	43.00%	38.49%	-
Some college (1-3 years college)	16.04%	22.04%	-
University graduate (bachelor degree or equivalent)	17.06%	17.43%	-
Postgraduate, master's degree, doctorate	3.75%	3.29%	-
Refuse to answer	0.00%	0.33%	-
Household income			
< $1,500/month	50.00%	51.19%	-
$1,500 - $2,999/month	31.91%	34.13%	-
≥ $3,000/month	3.95%	2.73%	-
Don't know/refuse to answer	14.14%	11.95%	-
Average	$1,679	$1,662	$1,784
Price typically paid for a shawarma sandwich			
LBP1,500 - LBP3,000	22.53%	21.71%	-
LBP3,500 - LBP5,000	74.06%	73.36%	-
LBP5,500+	3.41%	4.93%	-

* Sample figures in bold are significantly different from the Greater Beirut figure at the 5 percent confidence level.

3. Model Specification and Estimation

The approach we follow here is essentially a hybrid approach which takes elements from both Balcombe, et al. (2011), Balcombe, et al. (2014) and Balcombe, et al. (2015a) in that it uses both ranking and non-attendance data to construct a multiplicative weight. The utility (U) that the j^{th}

(j=1,....,J) individual receives from the i^{th} choice (i=1,...,I) in the s^{th} choice set (s=1,....,S) is assumed to be of the form

$$U_{ijs} = \dot{x}'_{ijs}\dot{g}\left(\beta_j\right) + e_{ijs} \tag{1}$$

where $\dot{x}_{ijs}$ denotes the K×1 vector of attributes presented. The error e_{ijs} is 'extreme value' (Gumbel) distributed, is independent of $\dot{x}_{ijs}$, and is uncorrelated across individuals or across choices. β_j is a (k×1) vector describing the preferences of the j^{th} individual and obeys:

$$\beta_j = \alpha + u_j \tag{2}$$

where α is the mean and u_j is an independently (across j) and identically normally distributed vector with variance covariance matrix Ω. The function $\dot{g}\left(\beta_j\right) = \left(\dot{g}_1\left(\beta_{1j}\right), \ldots\ldots, \dot{g}_K\left(\beta_{Kj}\right)\right)$ is a dimension-preserving transformation of the vector β_j. For example, by using an exponential transformation for a given attribute coefficient, the marginal utility for that attribute becomes log-normal. The errors $\{u_j\}$ are assumed to be uncorrelated across individuals. It is also common to condition the marginal utility in (2) on variables that characterize the respondent, as we discuss below.

With respect to the ranking data $\{z_{jk}\}$, where z_{jk} is the ranking of the k^{th} attribute by the j^{th} individual (with z_{jk}=1 indicating the highest ranked attribute) as in Balcombe, et al. (2014), the weighting factor from the ranking data is defined by $\left(\bar{\lambda}_{j1}, \ldots\ldots, \bar{\lambda}_{jK}\right)$. These are constructed from the elements:

$$\bar{\lambda}_{jk} = \left(1-\tau\right) + \tau \frac{\left(K - z_{jk}\right)}{K-1} \tag{3}$$

where τ is a parameter that is to be estimated and is free to vary between zero and one. As $\tau \rightarrow 0$, the ranking data become unimportant in determining the mean and variance of the coefficients. At the other extreme, τ=1 implies that the lowest ranked attribute has zero marginal utility. The second weighting factor is $\left(\tilde{\lambda}_{j1}, \ldots\ldots, \tilde{\lambda}_{jK}\right)$ constructed using the stated non-attendance data (where δ_{jk}=1 if non-attendance is stated and δ_{jk}=0 otherwise):

$$\tilde{\lambda}_{jk} = \rho\delta_{jk} + \left(1-\delta_{jk}\right) \tag{4}$$

It then follows that the individual marginal utilities are modelled by assuming $g\left(\beta_j\right)=\left(g_1\left(\beta_{j1}\right),.....,g_K\left(\beta_{jK}\right)\right)$ where g_k is a transformation (e.g. an exponential) and likewise defining the elements of $\dot{g}\left(\beta_j\right)$:

$$\dot{g}_k\left(\beta_{jk}\right)=\lambda_{jk}g_k\left(\beta_{jk}\right) \tag{5}$$

$$\lambda_{jk}=\bar{\lambda}_{jk}\tilde{\lambda}_{jk} \tag{6}$$

We note that for the highest ranked attribute, $\bar{\lambda}_{jk}=1$ regardless of the value of τ. Without this condition the model would not be identified. We note that a similar condition is employed by Layton (2000) in his examination of DCE rank data. We refer to this model format as the ‘contraction approach'. We can write this in vector form using:

$$\dot{g}\left(\beta_j\right)=\Lambda_j g\left(\beta_j\right) \tag{7}$$

$$\Lambda_j=diag(\lambda_{j1},.......\lambda_{jK}) \tag{8}$$

3.1 Restrictions and sub-models

Models can be differentiated according to the nature of $g()$ along with restrictions on how non-attendance data and ranking data are used. There are five particular sub-models that are of interest:

- M1: No use of ANA or ranking data $\tau = 0$, $\rho = 1$
- M2: Use of ANA data only, under ANA equals zero utility $\tau = 0$, $\rho = 0$
- M3: Use of ANA data only $\tau = 0$, $\rho \in [0,1]$
- M4: Use of ranking data only $\rho = 1$, $\tau \in [0,1]$ free
- M5: Joint use of both ranking and ANA data ($\rho \in [0,1]$, $\tau \in [0,1]$)

3.2 Estimation

The model is simple to estimate using Bayesian methods, since it can be specified in a similar way to the standard Mixed Logit, with the normal latent variables being multiplied by the contraction terms. As outlined in the previous section the prior distribution for the latents is assumed to be:

$$\beta_j \sim N(\alpha, \Omega) \tag{9}$$

The utility is:

$$U_{ijs} = \left(\dot{x}_{ijs}' \Lambda_j\right) g\left(\beta_j\right) + e_{ijs} \tag{10}$$

By defining:

$$x_{ijs}' = \dot{x}_{ijs}' \Lambda_j \tag{11}$$

the non-stochastic component of utility is defined conventionally as:

$$V_{ijs} = x_{ijs}' g\left(\beta_j\right) \tag{12}$$

and the posterior densities for the parameters $\{\beta_j\}$, α, Ω and τ are obtained by observing that the probability of i being chosen in the circumstance js is the standard logit probability:

$$p_{ijs} = \frac{e^{V_{ijs}}}{\left(\sum_i e^{V_{ijs}}\right)} \tag{13}$$

If the observed choices are defined by y_{ijs}=1, where the i^{th} option is chosen in circumstance js and y_{ijs}=0 otherwise, then the likelihood of all the observed choices (Y) is:

$$f\left(Y \mid \tau, \alpha, \Omega\right) = \prod_i \prod_j \prod_s p_{ijs}^{y_{ijs}} \tag{14}$$

Conditional on Λ_j, the steps for generating latent variables $\{\beta_j\}$ along with α and Ω can be estimated using Markov Chain Monte Carlo (MCMC) steps as in the standard Mixed Logit (e.g. Train and Sonnier (2005)). That is, having normalized the attributes $\left(x_{ijs}' = \dot{x}_{ijs}' \Lambda_j\right)$, the conditional distributions for β_j along with α and Ω are defined in the usual way (in terms of x_{ijs}). However, since τ is estimated, the normalized attributes need to be updated at each iteration, and the posterior distribution for τ is also required. The precision matrix has a Wishart prior $W(I,k+4)$ where k is the dimension of the covariance matrix. The precise priors that we use have a mean of zero for α and a diagonal covariance matrix for α with a variance of 100 for each of the effects common to all models. For the covariate terms in the model using the ranking data (M2) the variances were set to 10. Thus, the prior variance for α was set so as to be relatively uninformative for the estimates, and small enough so that the penalty for additional parameters in the model would not be very restrictive.

Both τ and ρ lie on the unit interval for which we assign independent uniform priors. Our priors on ρ and τ are independent since we have no prior basis to assume that they are correlated. Obviously, rankings and stated ANA will be related but this does not imply that higher ρ values will imply higher τ values or vice versa. Importantly, however, they are not assumed to be independent in estimation. That is, they can be correlated in their posterior distributions. It follows that the posterior distributions for θ=(τ,ρ) is:

$$f\left(\theta \mid Y, \alpha, \Omega\right) \propto f\left(Y \mid \theta, \alpha, \Omega\right) f\left(\theta\right) \tag{15}$$

where $f(\theta)$ has a uniform prior over the unit interval [0,1]×[0,1]. Estimation proceeds by iterating through the sequence of conditional draws: $\{\beta_j\}|\alpha,\Omega,\theta,Y$; $\alpha|\{\beta_j\},\Omega,\theta,Y$; $\Omega|\{\beta_j\},\alpha,\theta,Y$; $\tau|\alpha,\Omega,\{\beta_j\},Y$. The conditional posterior distributions for the first three components are the same as in Train and Sonnier (2005). The conditional posterior distribution for θ is obtained from **Error! Reference source not found.**. These can be sampled using Metropolis-Hastings steps with a random walk proposal density[5].

4. Results

4.1 Non-attendance and ranking of attributes

We begin with an analysis of the non-attendance and ranking data, for which the mean values are given in Table 3. In what follows we shall use the term attended or non-attended in the 'stated' sense. The column labelled ANA represents the proportion of respondents stating non-attendance for the attribute in question. The ranking column is the mean rank of the attribute in question (1 being the highest ranked). These results are broadly similar across the two treatments (with and without risk attribute). In both treatments location was on average the least attended and the lowest ranked. The risk variable was the most highly attended to and also the highest ranked when included, but when not included the certificate attribute was the highest ranked and most attended

[5] All models were estimated using a burn-in of 100,000 iterations followed by 2 million iterations from which a draw was taken every 200th iteration. Convergence was monitored by formal tests and visual plots.

to. We note the relatively high levels of ANA for the location and convenience attributes, especially in the ‘with risk attribute’ treatment. This seems to concur with findings by De Bekker-Grob, et al. (2010). They argue that respondents have a high propensity to ignore certain attributes in labelled experiments, as in the case of our study in which the various safety certificates are used to label alternatives. However, this contrasts with the very low ANA level for another attribute, namely risk, suggesting that labelling may not necessarily trigger a uniform, across-the-board, increase in ANA across all attributes.

Table 3. Average ANA and attribute ranking per attribute

	With risk attribute		Without risk attribute	
Attribute	ANA	Ranking	ANA	Ranking
Price	0.216	3.236	0.213	2.551
Certificate	0.158	2.185	0.070	1.512
Location	0.551	3.993	0.401	2.979
Size	0.469	3.925	0.345	2.962
Risk	0.027	1.664	-	-

Comparing across the two treatments, perhaps the most noticeable shift in pattern is the increased attendance to certification as a result of dropping risk. In addition, introducing the risk variable increased non-attendance for location and size, even though risk has itself a very high attendance. This would be consistent with the hypothesis that as complexity increases, respondents adopt simplifying strategies. In the case at hand the introduction of risk has possibly lead respondents to focus less on certification, location and size, yet maintain the same focus on price. However, such a conclusion is only tentative, since stated ranks and attendance may not be perfectly accurate indicators of respondents' emphases on attributes.

In Table 4 we see a proportion of individuals not attending to a number of attributes along with the total proportion of respondents not attending to at least one attribute. Overall these indicate that many respondents tended not to attend to multiple attributes and that a slight majority of respondents ignored at least one attribute. Notably, we have a proportion of individuals in both treatments that only used one attribute, but this was particularly so in the ‘without risk attribute’ treatment. Another useful exercise is to evaluate the consistency between the stated ANA and ranking data. One would expect that if a respondent indicates non-attendance to an attribute, then the ranking for that attribute should be worse than the rankings for all attributes that are attended. This indeed turned out to be the case for all respondents except for one respondent in the 'with risk attribute' treatment. Thus the non-attendance and ranking data were very internally consistent.

Table 4. Proportion of ANA in the sub-sample by number of non-attended attributes

Nr. of non-attended attributes	Without risk attribute	With risk attribute
1	0.167	0.151
2	0.153	0.209
3	0.185	0.229
4	0.000	0.041
5	-	0.000
Total	0.505	0.630

4.2 Choice model results

Next we turn to the estimates of the models from the two choice experiments. We evaluated our models on the basis of their Log Marginal Likelihood (LML). We estimated the models under the assumption of normal and log-normal marginal utilities for the non-price and price attributes, respectively[6]. Five models were estimated for each of the two choice experiments. The LML results are presented in Table 5. Readers are reminded that the marginal likelihood has an implicit penalty for additional parameters. Therefore, the model with the highest LML is the preferred model. The posterior odds of any two models given equal prior odds can be calculated by taking the exponent of the difference of the two marginal likelihoods. Differences of 3 or more translate into very large posterior odds in favour of the model with the larger marginal likelihood.

Table 5. Log marginal likelihoods of the various models estimated

Estimated model	With risk attribute	Without risk attribute
No ANA or rankings (M1)	-2561.88	-2374.19
ANA only (M2)	-2542.48	-2341.96
ANA only (M3)	-2459.96	-2315.69
Rankings only (M4)	-2484.12	-2300.66
Joint use of ANA and rankings (M5)	-2433.49	-2285.62

[6] In order to make a more robust evaluation vis-à-vis ranking and non-attendance, we also estimated all five models (M1-M5) imposing a normal distribution for price. The LML values were consistently higher for the lognormal-price specifications compared to their normal-price counterparts, indicating an improved model fit. More importantly, the LML values ranked the same across both specifications for all five models. This suggests that determining the preferred type of model is robust to this assumption. We therefore only discuss the lognormal-price specifications.

Note that the 'without' and 'with risk attribute' treatments should not be compared using the marginal likelihoods as they are separate data sets. Common to both treatments is that the model that does not utilise either ANA or ranking information is inferior to any of the models that employ ranking or ANA data either singularly or jointly. This is because the first row in each table is the smallest (most negative) value by a considerable margin. The next worst performing models are those employing ANA but imposing ρ=0 (M2). Thus, while models employing ANA are preferred, stated ANA is not consistent with zero marginal utility for that attribute in line with previous findings.

Next we compare models that exclusively use ANA data or ranking data (Models M3 and M4). In this instance, the 'with risk attribute' treatment supports the use of ANA data whereas the 'without risk attribute' treatment supports the use of the ranking data. This highlights that neither ANA nor ranking data should be seen as clearly superior. Further to this, for both data sets we see that model M5 that employs both types of information is preferred across both data sets. Thus, while ranking and ANA data were highly consistent, they do not replicate each other or substitute for one another. Indeed due to the imprecision of stated ANA (that in turn may be due to an incorrect way of gathering it or to errors made by respondents) and the assumed independence of the prior distributions of ρ and τ, model M5 holds a larger 'flexibility' relative to the other models, which allows it to better fit the data. So, the utility of using both ANA and ranking is this larger flexibility which allows 'improving' the quality of the stated information.

We give the estimates of the parameters for ρ and τ in Table 6. These are taken from the models with the log-normal price coefficient, but the choice of distribution has only a very small impact on these parameters. First, as we can see from the model containing only ANA (M3) the estimates for ρ are 0.259 and 0.436 for the 'without risk attribute' and 'with risk attribute' treatments respectively. Thus the higher rates of ANA in the 'with risk attribute' treatment are accompanied by the estimation of a lower impact of ANA on the parameter estimates. This perhaps suggests that while stated ANA increases with the complexity of the experiment, this stated ANA does not actually reflect a lower weight being given to attributes in the experiment, but rather a shift in ex-post reporting. The estimates of τ from Model (M4) are 0.58 and 0.57 for the 'without risk attribute' and 'with risk attribute' treatments, suggesting that this parameter is more stable to the increased dimensionality of the choice task. The model (M5) for the with risk and without risk attribute data shows a shift upward in the values of ρ and a shift downward in the values of τ. This is to be expected given the relationship between the reporting of ANA and ranking data. Since respondents who report ANA are also likely to give an inferior ranking to the importance of that attribute, the overall downward weighting of the marginal utility will be reflected by the joint effects.

Table 6. ρ and τ^{*} estimates for various model types (standard deviations in parentheses)

	Without risk attribute		With risk attribute	
Estimated model	ρ	τ	ρ	τ
M3	0.259	-	0.436	-
	(0.029)	-	(0.051)	-
M4	-	0.585	-	0.570
	-	(0.033)	-	(0.041)
M5	0.334	0.413	0.547	0.481
	(0.049)	(0.038)	(0.066)	(0.051)

[*] The intuition underlying the ρ and τ parameters is as follows. Both the ranking and non-attendance functions act to 'shrink' the distributions of the marginal utilities so that they have means closer to zero and are more densely packed around their means, provided people state that they do not attend an attribute and\or rank it as less important. The degree of 'shrinkage' is determined inversely in relation to ρ and positively in relation to τ. Both parameters are bounded by 0 and 1. Therefore, at ρ=1and τ=0, there is no shrinkage, meaning that the stated ANA or rankings of individuals have no impact on the distributions. At ρ=0, a non-attender will have zero marginal utility for that attribute, i.e. s/he is as if s/he really ignored that attribute. At τ=1, the lowest ranked attribute will have zero marginal utility, with each of the other attribute moving towards their untransformed distribution incrementally and linearly with their ranking. The closer ρ is to 0, the greater the information contained in the stated ANA data, and the closer τ is to 1 the greater the influence of the ranking data. ρ and τ can therefore be thought of as average weighting factors for ANA and ranking, respectively.

Table 7. Parameter values and WTP across the treatments

	Without risk attribute				With risk attribute			
	α				α			
Attribute	Mean	Std. dev.	Ω	Median WTP	Mean	Std. dev.	Ω	Median WTP
Price (LBP'1,000s)	0.646	0.072	0.697	-	0.324	0.090	1.005	-
Certificate 2 (third-party local)	7.043	0.916	28.145	LBP 4,160	1.156	0.819	28.570	LBP 559
Certificate 3 (int'lly-recognized)	10.750	0.983	38.145	LBP 6,410	3.560	0.842	27.790	LBP 1,940
Certificate 4 (upgraded MoPH)	10.320	0.946	29.980	LBP 6,290	3.320	0.838	28.470	LBP 1,751
Location 2 (within walking distance)	0.649	0.178	0.803	LBP 166	1.164	0.333	2.800	LBP 349
Location 3 (need to go there by car)	-2.108	0.302	5.521	-LBP 622	0.915	0.314	1.660	LBP 274
Location 4 (delivery order)	-0.301	0.250	0.635	-LBP 72	-1.498	0.398	6.430	-LBP 488
Size (medium-sized)	2.195	0.225	2.739	LBP 757	2.240	0.251	1.590	LBP 978
Risk (%)	-	-	-	-	0.132	0.011	0.016	LBP 96

Finally, the parameters for the mixed logit are presented for the two groups in Table 7 for the log normal price models from M5. The α and Ω are as defined in the theoretical section and the median WTP is calculated by means of simulation using the sample mean values for non-attendance and rankings[7]. Because prices were divided by 1000, the WTP values, which are attribute to price parameter ratios, were multiplied by 1000 to express them as actual monetary values. For the dummy variables the WTP for the certificate variables are relative to having no certificate; the location relative to location 1 (round the corner), and (portion) size a medium-sized sandwich relative to a regular small-sized sandwich. For (foodborne) risk in the with risk attribute treatment, on the other hand, the willingness to pay of LBP96 is for a 1% reduction in risk. Therefore a 20% reduction in risk is worth approximately LBP1,920 to an average respondent.

Beginning with the non-safety attributes location and size, respondents in both treatments seem to attach to them considerably lower WTP magnitudes than the safety attributes certificate and risk. In terms of location, any location pair commands a WTP value that is below LBP850. An interesting result pertaining to location is worth noting. In the 'without risk attribute' treatment, the positive coefficient for 'location 3' is negative, as is expected; respondents expect a discount for going by car to a food outlet to purchase a shawarma sandwich. Yet in the 'with risk attribute' treatment, discount is counter-intuitively turned into premium. We speculate that the addition of a

[7] The WTP estimates are obtained by drawing 50,000 normally distributed latent variables from their posterior distribution. These are then transformed (if necessary) before obtaining the mean and median of the ratios of the marginal utility of each attribute divided by the marginal utility of price.

quantitative risk attribute may have ‘fully’ sensitized respondents to the safety dimension compared to the ‘without risk attribute’ treatment. In a mediatic climate punctuated by periodic food scares (especially since late 2009), many such sensitized respondents may start trusting shawarma vendors that are further afield, perceiving them, for right or wrong, as safer than the ones next door. As for size, WTP for a medium-sized sandwich compared to a regular small-sized sandwich amounts to LBP760 and LBP980 in the without and with risk attribute treatments respectively.

Turning to the safety attributes in the ‘without risk attribute’ treatment, results indicate a WTP of LBP4,160, LBP6,400 and LBP6,200 extra for third-party local (Certificate 2), internationally recognized (Certificate 3) and upgraded MoPH (Certificate 4) certified sandwiches, respectively. It is worth noting that consumers in Greater Beirut pay an average of LBP4,000 for a typical shawarma sandwich, which means these WTPs range between 100% and 155% of the current prices of uncertified sandwiches. In the ‘with risk attribute’ treatment, these WTPs drop to LBP560, LBP1,940 and LBP1,750. In both treatments, the WTP for an upgraded MoPH sandwich is slightly smaller than for one with an internationally recognized certificate, though the attributes’ descriptions clearly state that the two certification schemes involve virtually the same service provided with the same level of rigour. As is typically the case in many developing countries, this no doubt reflects scepticism on the part of Lebanese consumers about the ability of the state to deliver on its promises, be it in the area of food safety or any other public arenas.

We should not be surprised at the change in the WTPs across the two treatments once risk reductions are taken into account. When no explicit risk reduction is in the treatment, then certification is probably taken as a proxy for risk reduction. However, when explicit risk reduction is introduced, then arguably the role of certification in determining WTP is substantially downgraded. On the other hand, if risk reductions attendant to these certification schemes are accounted for, typically in the order of 20% for Certificate 2 and 70% for Certificates 3 and 4, WTPs increase substantially. Therefore for Certificate 2 and a typical reduction of 20% in risk, and according to the ‘with risk attribute’ results, people will be willing to pay a combined LBP560+LBP1,920=LBP2,480. Likewise, WTPs for Certificates 3 and 4 become LBP8,660 and LBP8,470 respectively. These numbers suggest that the presence of explicit risk information further valorises safety certification, especially where this certification scheme is seen to be rigorous by consumers.

5. Conclusion

This paper investigated the alternative and possibly joint use of non-attendance and ranking data to improve estimates of preference parameters for individuals. As with most previous studies, stated attribute non-attendance was found not to be consistent with having zero utility, thus reinforcing the message that the use of stated non-attendance responses should not enforce this condition. It also showed that the degree to which people respond to non-attendance questions can change depending on the nature of the experiment, even if the changes are relatively small. We found that while responses to the two questions were highly consistent, neither was considered superior across both data sets employed in this study, and the joint use of both types of data improved estimates of preference parameters.

The correspondence between ranking data and non-attendance was high, but nonetheless, the marginal utility of a respondent who indicates non-attendance and ranks the attribute as relatively unimportant, has a lower marginal utility than one who indicates that they did not attend to the attribute, yet gives it a comparatively high ranking. We view this relative incongruence between these two sources of information as a positive feature of our model. Indeed such incongruence would justify, rather than undermine, the simultaneous use of these two data sources if the modelling framework within which they are incorporated is adequately specified.

We therefore recommend that researchers consider both forms of follow-up questions when implementing choice experiments, and that these questions be employed in the subsequent analysis. Here we have introduced one such approach, and provided evidence that it works well. While our approach used a modification of the mixed logit, it is more widely applicable to other discrete choice models, including the latent class model (LCM). Moreover, this approach can accommodate a broad variety of information sources to capture respondents' and consumers' attention to various attributes of choice tasks or products. Eye-tracking data are a case in point (Balcombe, et al., 2015b), and future research in this area should look into creative ways of harnessing other indicators of attribute attendance, attention, importance and the like.

References

Abiad, M., & Chalak, A. (2012). Unraveling mean and variance heterogeneity influences of information provision on safer food purchasing decisions: A heteroscedastic mixed logit approach. *Food Economics, 9*(3), 135-144.

Alemu, M. H., Mørkbak, M. R., Olsen, S. B., & Jensen, C. L. (2013). Attending to the reasons for attribute non-attendance in choice experiments. *Environmental and Resource Economics, 54*(3), 333-359.

Angulo, A. M., & Gil, J. M. (2007). Risk perception and consumer willingness to pay for certified beef in Spain. *Food Quality and Preference, 18*(8), 1106-1117.

Baker, G. A. (1999). Consumer preferences for food safety attributes in fresh apples: market segments, consumer characteristics, and marketing opportunities. *Journal of Agricultural and Resource Economics*, *24*(1), 80-97.

Balcombe, K., Bitzios, M., Fraser, I., & Haddock-Fraser, J. (2014). Using attribute importance rankings within discrete choice experiments: An application to valuing bread attributes. *Journal of Agricultural Economics*, *65*(2), 446-462.

Balcombe, K., Burton, M., & Rigby, D. (2011). Skew and attribute non-attendance within the Bayesian mixed logit model. *Journal of Environmental Economics and Management, 62*(3), 446-461.

Balcombe, K., Fraser, I., Lowe, B., & Souza Monteiro, D. (2015a). Information customization and food choice. *American Journal of Agricultural Economics*.

Balcombe, K., Fraser, I., & McSorley, E. (2015b). Visual attention and attribute attendance in multi-attribute choice experiments. *Journal of Applied Econometrics, 30*(3), 447-467.

Campbell, D., Aravena, C. D., & Hutchinson, W. G. (2011a). Cheap and expensive alternatives in stated choice experiments: Are they equally considered by respondents? *Applied Economics Letters*, *18*(8), 743-747.

Campbell, D., Hensher, D. A., & Scarpa, R. (2011b). Non-attendance to attributes in environmental choice analysis: A latent class specification. *Journal of Environmental Planning and Management, 54*(8), 1061-1076.

Chalak, A., & Abiad, M. (2012). How effective is information provision in shaping food safety related purchasing decisions? Evidence from a choice experiment in Lebanon. *Food Quality and Preference, 26*(1), 81-92.

Collins, A. T., Rose, J. M., & Hensher, D. A. (2013). Specification issues in a generalised random parameters attribute nonattendance model. *Transportation Research Part B: Methodological*, *56*, 234-253.

Colombo, S., & Glenk, K. (2013). Social preferences for agricultural policy instruments: Joint consideration of non-attendance to attributes and to alternatives in modelling discrete choice data. *Journal of Environmental Planning and Management*.

De Bekker-Grob, E. W., Hol, L., Donkers, B., Van Dam, L., Habbema, J. D. F., Van Leerdam, M. E., et al. (2010). Labeled versus unlabeled discrete choice experiments in health economics: An application to colorectal cancer screening. *Value in Health, 13*(2), 315-323.

Enneking, U. (2004). Willingness-to-pay for safety improvements in the German meat sector: the case of the Q&S label. *European Review of Agricultural Economics, 31*(2), 205-223.

Ferrini, S., & Scarpa, R. (2007). Designs with a priori information for nonmarket valuation with choice experiments: a Monte Carlo study. *Journal of Environmental Economics and Management, 53*(3), 342-363.

Goldberg, I., & Roosen, J. (2007). Scope insensitivity in health risk reduction studies: A comparison of choice experiments and the contingent valuation method for valuing safer food. *Journal of Risk and Uncertainty, 34*(2), 123-144.

Hanley, N., Mourato, S., & Wright, R. E. (2001). Choice modelling approaches: a superior alternative for environmental valuation? *Journal of Economic Surveys, 15*(3), 435-462.

Hensher, D. A. (2010). Hypothetical bias, choice experiments and willingness to pay. *Transportation Research Part B: Methodological*, *44*(6), 735-752.

Hensher, D. A., Collins, A. T., & Greene, W. H. (2013). 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), 1003-1020.

Hensher, D. A., & Greene, W. H. (2010). Non-attendance and dual processing of common-metric attributes in choice analysis: A latent class specification. *Empirical Economics, 39*(2), 413-426.

Hensher, D. A., Rose, J., & Bertoia, T. (2007). The implications on willingness to pay of a stochastic treatment of attribute processing in stated choice studies. *Transportation Research Part E: Logistics and Transportation Review, 43*(2), 73-89.

Hensher, D. A., Rose, J., & Greene, W. H. (2005). The implications on willingness to pay of respondents ignoring specific attributes. [Article]. *Transportation, 32*(3), 203-222.

Hensher, D. A., & Rose, J. M. (2009). Simplifying choice through attribute preservation or non-attendance: Implications for willingness to pay. *Transportation Research Part E: Logistics and Transportation Review, 45*(4), 583-590.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2012). Inferring attribute non-attendance from stated choice data: Implications for willingness to pay estimates and a warning for stated choice experiment design. *Transportation, 39*(2), 235-245.

Hess, S., & Hensher, D. A. (2010). Using conditioning on observed choices to retrieve individual-specific attribute processing strategies. *Transportation Research Part B: Methodological, 44*(6), 781-790.

Hess, S., & Hensher, D. A. (2013). Making use of respondent reported processing information to understand attribute importance: A latent variable scaling approach. *Transportation, 40*(2), 397-412.

Hess, S., Stathopoulos, A., Campbell, D., O'Neill, V., & Caussade, S. (2013). 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.

Hole, A. R. (2011). A discrete choice model with endogenous attribute attendance. *Economics Letters, 110*(3), 203-205.

Jaeger, S. R. (2006). Non-sensory factors in sensory science research. *Food Quality and Preference, 17*(1-2), 132-144.

Kehlbacher, A., Balcombe, K., & Bennett, R. (2013). Stated attribute non-attendance in successive choice experiments. *Journal of Agricultural Economics, 64*(3), 693-706.

Kragt, M. E. (2013). Stated and inferred attribute attendance models: A comparison with environmental choice experiments. *Journal of Agricultural Economics, 64*(3), 719-736.

Lagarde, M. (2013). Investigating attribute non-attendance and its consequences in choice experiments with latent class models. *Health Economics, 22*(5), 554-567.

Layton, D. F. (2000). Random coefficient models for stated preference surveys. *Journal of Environmental Economics and Management*, *40*(1), 21-36.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated Choice Methods: Analysis and Applications*. Cambridge: Cambridge University Press.

MoSA, CAS, UNDP, & ILO. (2008). The National Survey of Households' Living Conditions 2007. Report on Households' Living Conditions. Beirut, Lebanon. Ministry of Social Affairs, Central Amdinistration of Statistics, United Nations Development Programme and International Labor Organization.

MoSA, UNDP, & CAS. (2006). Living Conditions of Households. The National Survey of Households Living Conditions 2004. Beirut, Lebanon. Ministry of Social Affairs, United Nations Development Programme and Central Amdinistration of Statistics.

Notermans, S., Gallhoff, G., Zwietering, M. H., & Mead, G. C. (1995). Identification of critical control points in the HACCP system with a quantitative effect on the safety of food-products. [Article]. *Food Microbiology, 12*(2), 93-98.

Redmond, E. C., & Griffith, C. J. (2004). Consumer perceptions of food safety risk, control and responsibility. *Appetite, 43*(3), 309-313.

Scarpa, R., Gilbride, T. J., Campbell, D., & Hensher, D. A. (2009). Modelling attribute non-attendance in choice experiments for rural landscape valuation. *European Review of Agricultural Economics, 36*(2), 151-174.

Scarpa, R., Zanoli, R., Bruschi, V., & Naspetti, S. (2013). Inferred and stated attribute non-attendance in food choice experiments. *American Journal of Agricultural Economics, 95*(1), 165-180.

Teisl, M. F., & Roe, B. E. (2010). Consumer willingness-to-pay to reduce the probability of retail foodborne pathogen contamination. *Food Policy, 35*(6), 521-530.

The Daily Star. (2014, November 11). Health minister: Lebanon's food 'dipped in diseases and microbes', *The Daily Star*. Retrieved from http://www.dailystar.com.lb/News/Lebanon-News/2014/Nov-11/277240-lebanese-are-eating-diseased-food-health-minister.ashx

Train, K. E., & Sonnier, G. (2005). Mixed logit with bounded distributions of correlated partworths. In R. Scarpa & A. Alberini (Eds.), *Applications of Simulation Methods in Environmental and Resource Economics* (pp. 117-134). Dordrecht: Springer.

WHO. (2011). World Health Organization (2010). Food Safety <http://www.who.int/foodsafety/en/> Retrieved August 10th, 2011.