"Using Experiments to Address Attribute Non-attendance in Consumer Food Choices"

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Abstract

A number of choice experiments (CEs) studies have shown that survey respondents employ heuristics such as attribute non-attendance (ANA) while evaluating food. This paper addresses a set of methodological questions. First, it explores if ANA is an issue to take into account in food valuation studies. Second, it assesses if there is any difference in terms of welfare estimates between the two common ways of collecting self-reported stated ANA (serial and choice task). Next, it validates the statements of ANA behavior provided by the respondents across serial and choice task self-reported ANA. Lastly, it explores the issue of concordance between the stated ANA and inferred ANA methods. We estimated a set of choice models including inferred or observed ANA information. Our results show a clear winner between the two stated approaches, choice task, which also better matches the inferred ANA data.

Key words: serial stated attribute non-attendance, choice task attribute non-attendance, , inferred attribute non-attendance, food choice experiments, , food labeling

In modeling food choice it is obviously necessary to have an adequate understanding of what food features are actually evaluated by agents who are making choices. Such understanding constitutes the foundation upon which suitable individual utility functions might be developed. This important consideration has often been neglected in food choice, especially in the practice of stated preference surveys using choice experiments (CEs). As a way to progress research in this area, we examine two alternative ways of collecting information about what food attributes are and are not paid attention to during a specifically designed set of food CEs. In the broader CE literature this manner of processing attributes is commonly called "attribute non-attendance" (ANA) behavior. This term is used when respondents ignore some of the food attributes used to describe the product profiles while evaluating the set of alternatives in a choice task to which they are exposed during an experiment. While this issue has been studied in other CE applications (i.e., environmental, transportation, and health economics literature), it has not been given extensive attention in food choice. Scarpa et al. (2013) is the only food choice study that compared the stated ANA method (i.e., serial ANA) and inferred ANA approach. No other known study however has examined the ANA issue in consumer food choice at both the serial and choice task levels. This is an important topic since the use of CEs in consumer food choice settings has significantly increased in the last decade. With this study we contribute to the food choice literature by comparing two stated ANA approaches (serial and choice task ANA) and the concordance of ANA forecasts between the two stated ANA methods and the inferred ANA approach. .

A common assumption when analyzing CE data is that respondents have paid attention to all presented attributes during the decision-making process, which is consistent with the continuity axiom of consumer behavior. Theoretically, this implies a fully compensatory behavior , whereby consumers are capable of processing and willing to process all the proposed attributes by trading off gains in one attribute with losses in another (Campbell and Lorimer 2009; Kragt 2013). Practically, this requires the decision-makers to make a considerable mental effort and have an unlimited processing capacity (Shah and Oppenheimer 2008) in accessing all the proposed attributes. However, these two assumptions may well be unfounded and difficult to corroborate in the experimental practice.

Recent studies have shown that decision-makers lack both the ability and the cognitive resources to optimize their decision and to formulate accurate judgments based on all proposed attributes (Cameron and DeShazo 2010). For example, respondents have been found to behave in a rationally adaptive manner by seeking to minimize cognitive cost of choice and maximize benefit while making choices (DeShazo and Fermo 2004). A number of CE studies have also argued that it is neither entirely persuasive nor realistic to assume that respondents attend to all the information described in the alternatives during the conduct of a CE. Survey respondents may employ diverse attribute processing heuristics when making choices such as ANA, resulting in a violation of the continuity axiom. As argued by Campbell, Hutchinson, and Scarpa (2008) ignoring attributes in the choice set implies non-compensatory behavior and respondents using such discontinuous preference cannot be represented by a conventional utility function.

In this respect, data from several CEs have indicated that not accounting for such discontinuity preferences may result in bias as it significantly impacts willingness to pay (WTP) estimates for specific attributes (Hensher, Rose and Greene 2005; Hensher 2006, Hensher, Rose, and Bertoria 2007; Puckett and Hensher 2008; Hensher and Rose 2009; Scarpa et al. 2009; Hess and Hensher 2010). Additional evidence also indicates that econometric specifications incorporating ANA behavior tends to improve discrete choice model fits (Scarpa, Thiene, and Hensher 2010). However, the literature offers contradictory findings since the direction of the effect of accounting for ANA on WTP estimates is mostly empirical (Scarpa, Thiene, and Hensher 2010). For example, DeShazo and Fermo (2004), Rose, Hensher, and Greene (2005) and Hensher Rose, and Bertoria (2007) found higher estimates of marginal WTPs when accounting for ANA in modeling choice, while others documented lower estimates of marginal WTPs (Campbell, Hutchinson, and Scarpa 2008; Campbell and Lorimer 2009). Hence, addressing ANA is of consequence for both market share predictions and welfare estimates (Scarpa et al. 2013).

The applied literature on choice modeling has made substantial progress in modeling ANA information in the field of transportation (Hensher, Rose, and Greene 2005; 2012; Hensher and Greene 2010; Hensher, 2006, 2008), environmental valuation (Campbell, Hutchinson, and Scarpa 2008; Scarpa et al. 2009; Scarpa, Thiene, and Hensher 2010; Carlsson, Kataria, and Lampi 2010; Campbell, Hensher, and Scarpa 2011) and health economics (Mc-Intoch and Ryan 2002; Lancsar and Louviere 2006; Hole 2011). Together, these studies provide important insights into the development of (i) different ways of modeling and accounting for ANA behavior, and (ii) various techniques to collect ancillary information and implement additional econometric analyses aimed at revealing different attribute processing behaviors resulting in ANA into the random utility framework.

Two methods for modeling ANA behavior have been defined in the literature: stated ANA and inferred ANA (Hensher 2006; Scarpa et al. 2009; Scarpa, Thiene, and Hensher 2010). The stated ANA refers to methods that account for ANA by asking respondents specific follow-up questions on whether or not an attribute was ignored when making a decision (e.g. self-reported statements on ANA), while inferred ANA refers to analytical models that "infer" ANA from the observed pattern of choices. Stated ANA can be monitored in CE surveys in two ways: at the serial and or choice task level. In the serial ANA approach, respondents are asked to report what attribute they feel they systematically disregarded in the whole sequence of choice tasks. This question is obviously asked to the respondent at the end of their choice task sequence. Instead, to implement the choice task ANA approach, respondents are asked which attributes they ignored after each individual choice task. While a considerable number of studies on serial ANA exist (Hensher, Rose, and Greene 2005; Hensher and Rose 2009; Scarpa et al. 2009), scant literature is available on choice task ANA (Puckett and Hensher 2008, 2009; Meyerhoff and Liebe 2009; Scarpa, Thiene, and Hensher 2010). Monitoring stated ANA at the choice task level is obviously laborious, but it might be a better approach than doing so only at the serial level. This is because, for example, ANA behavior by the same respondent may vary among the different choice tasks as the respondent might change her attribute processing rule during the choice experiment (Puckett and Hensher 2009). Although the collection of choice task ANA data takes more respondent effort compared to the serial ANA, the advantages of accounting for choice task ANA might outweigh its additional cost and effort (Scarpa, Thiene, and Hensher 2010).

However, some authors have raised concerns about the reliability of the responses to the follow-up ANA questions in CE surveys (Hensher 2008; Hensher and Rose 2009; Hess and Hensher 2010). As such, several authors proposed the inferred approach as an alternative method to deal with ANA (Hensher and Greene 2010; Hess and Hensher 2010; Scarpa, Thiene, and Hensher 2010; Hensher, Rose, and Greene 2012). This method infers ANA behavior through the estimation of analytical models. Such models capture the probabilistic decision process in a latent class framework (Hess and Rose 2007; Scarpa et al. 2009; Hensher and Greene 2010; Campbell, Hensher, and Scarpa 2011; Hensher, Rose, and Greene 2012; Scarpa et al. 2009; Caputo, Nayga, and Scarpa 2013;), in which, different restrictions are imposed on the utility expressions for each attribute attendance class depending on the hypotheses on group adoption of pre-defined processing strategies. The growing body of literature using the latent class specification points towards a significant portion of people ignoring attributes (Scarpa et al. 2009; Caputo, Nayga, and Scarpa 2013).

Surprisingly, there is evidence suggesting that the inferred attribute processing strategies are not necessarily consistent with the responses given to follow up ANA questions. This issue has recently been challenged by Hess and Hensher (2010) by demonstrating that the inferred approach can lead to more consistent results and better fit since respondents who self-reported to have ignored some attribute may simply have attached less importance to it. However, more recently, Scarpa et al. (2013) compared the inferred and serial stated ANA methods and found that in their case there was no clear "winner" between these two approaches, even if the inference based on equality constrained latent class models better matches the observed data.

A better understanding of how to collect self-reported ANA information during the experiments (e.g. serial versus choice task) could improve the ways we design and analyze CE data. Also, addressing the issue of concordance between serial and choice task stated ANA as well as between the two stated ANA and and inferred ANA data is crucial in improving the behavioural relevance of CE models. Accordingly, in this study, we develop and implement two food CEs: : the *Serial Experiment* using the serial stated ANA approach, and the *Choice Task Experiment* using the choice task approach. In addition to the application in consumer food choice, this study also builds on previous research by addressing four main methodological ANA issues.

First, we investigate whether or not ANA is an issue of importance in food economics. Then, we explore whether there is any difference in terms of CE outcomes (e.g. WTPs; model performance) across the two forms of stated ANA (serial and choice task). Third, we validate the self-reported ANA statements across these two approaches using the stated ANA model approach suggested by Hess and Hensher (2010) with the intent to determine if there is any discrepancy between what survey respondents say they do and what they actually do when reporting ANA in CE surveys. Finally, we infer ANA in a latent class framework. To shed light on some of the outgoing debates about the concordance between the stated ANA and inferred ANA approach, we then compare the concordance of the frequencies at the sample level of the self-reported serial and choice task ANA information with those inferred from the estimation of two equality constraint latent class models (Scarpa et al. 2009; Caputo, Nayga, and Scarpa 2013). Given the relevant implications of not accounting for ANA in terms of welfare estimates in CE studies, this study makes a unique and original contribution to research on CE in terms of CE survey designs and choice model specifications.

This article is structured as follows. The next section reports the experimental procedures we used to set up the serial and the choice task experiments. This is then followed by a section that describes the empirical analysis. The results are then reported, followed by the conclusions.

Experimental Procedures

We constructed a CE study on a chicken breast product in Belgium against the background of growing consumer interest in sustainable food labeling. To describe each food profile, in addition to the price attribute, we used the following four attributes related to sustainable food labels: organic label, free range claim, carbon footprint label and EU animal welfare label. Since the last two labels are not yet present in the Belgian market, to study consumer's preference it was necessary to conduct a hypothetical CE study. Table 1 reports the attributes and levels of these attributes. For the organic label, three levels were considered, *OrgEU* is the variable for the EU organic logo introduced in 2010, the Belgian private Biogarantie logo or *OrgBE,* and no organic logo. The four levels for the free range claim included the three types of claim regulated in the EU food market (free range or *FR*, traditional free range or *FRtrad* and, free range-total freedom or *FRtot*) (EC, 2008b) and none. The levels for carbon footprint were based on reported values in the literature for producing a chicken breast (Foster et al. 2006) and adopt a 20% (*CO20*) and a 30% (*CO30*) carbon footprint reduction. The levels of the *Price* attribute were based on the chicken breast prices in food stores in Belgium in February 2012, shortly before the survey was conducted.

Based on these attributes, a CE design was performed following Street and Burgess (2007). Given the selected attributes and their levels, an orthogonal factorial design was developed for the first alternative, reducing the original 288 (3^2x4^2x2) combinations to just 16. Then, using the generators as described by Street and Burgess (2007) a practical set of 16 pairs was obtained, with a D-efficiency of 95.7%. Finally, the 16 choice sets were divided into two blocks and the participants were randomly assigned to one of the two blocks. To increase the similarity with a real shopping experience, a no-buy alternative was added to each choice set. Hence, each participant was presented with eight choice sets, where each choice set included two experimentally-designed product profiles and a no-buy option. A cheap talk script was included due to the hypothetical nature of our CE (Aprile, Caputo, and Nayga 2012; Silva et al. 2011; Van Loo et al. 2011). Before the choice set questions, basic information about the attributes was provided to the respondents.

The identification of stated ANA was obtained from supplementary ANA questions asking whether or not respondents ignored any specific attribute (see supplementary material). Respondents' statements about ANA were recorded in two different ways, resulting in two experiments, to which respondents were randomly assigned[1]. In experiment one, named *Serial Experiment* (serial ANA), ANA was monitored by asking the ANA questions at the end of the sequence of choice tasks. In experiment two, named *Choice Task Experiment* (choice task ANA), the ANA questions were recorded after each choice task (so a total of eight times).

Empirical Analysis

In this section, we illustrate the empirical models used to account for stated and inferred ANA. First, we specify three Random Parameter Logit models with Error Component model (RPL-EC). The first one assumes full attendance behavior while in the second one, the parameters for the ignored attributes are restricted to zero. The third model was used to validate the self-reported ANA provided by the respondents. In addition to the stated ANA, we infer ANA by specifying an equality constrained latent class models (ECLC). Both the stated and the inferred methods are in a panel structure to allow for the obvious correlation among individual preferences in a sequence of

[1] As a result, we have two datasets. One for the serial treatment and one for the choice task treatment. For models in which we do not want to account for stated ANA (full attendance model and latent class model), we only used the dataset from the serial treatment since respondents in the choice task treatment might have been triggered by the ANA questions asked during the CE.

choice decisions (eight choice sets in our case). In all the models the variable price, which refers to 1 kg of chicken breast, is treated as a continuous variable, while the rest of the qualitative labels are included in the model as dummy coded variables[2]. Data were analyzed using NLOGIT 5.0. For the estimation of the RPL-EC model, 250 Halton draws rather than pseudo-random draws are used since the former provides a more efficient simulation for this model (Bhat, 2003).

Modeling Serial and Choice task Stated ANA using a Random Parameter with Error Component Panel Logit Model

The serial and choice task CE data were estimated using an RPL-EC (Scarpa, Ferrini, and Willis 2005; Scarpa, Willis, and Acutt 2007), for a number of reasons. First, in our CE design the no-purchase option was included since some respondents might choose this option when shopping (Lusk and Schroeder 2004), leading them to a previously experienced reference point. The no-purchase option is actually experienced by participants while the experimentally designed alternatives are hypothetical. Thus, the utilities of the hypothetical options are likely to be more correlated between them than with the no-purchase-option and have a higher variance than the

[2] We used dummy coding rather that effect-coding, which is generally correct in static cross sectional multinomial logit models, since it is necessary for the use of the ANA restrictions to zero on the coefficient values. Posing this zero restriction on an effect-coded variable -1,1 would not be equivalent to a zero weight in the utility function, but to a weight which is intermediate between absence and presence of the attribute, and indeed collinear with the ASC (Caputo, Nayga, and Scarpa 2013). Also, in our case, the panel error component model has a shift from the zero baseline that is identified by the presence of a shared error component across all utilities of purchase. This shared error accounts for unobservable idiosyncratic conjectures that only belong to purchase options, thereby avoiding confounding.

utilities of the no-purchase-option. To capture the extra variance of the experimentally designed alternatives, Scarpa, Willis and Acutt (2007) suggested the use of an extra error component shared by the experimentally designed alternatives and missing in the utility of the no-purchase option. By identifying the additional variance of the utility of the experimentally designed alternatives, different from the no-purchase option, the RPL-EC accounts for correlation structure across utilities between the experimentally designed alternatives. Second, several studies of CE applications in environmental economics (Scarpa, Willis, and Acutt 2007; Hess and Rose 2008) and food choice (Scarpa, Thiene, and Maragon 2008; Caputo, Nayga, Scarpa 2013) have found error components of this type to consistently improve model fit in similar choice contexts. A good discussion of the rationale for this approach is reported in Marsh, Mkwara, and Scarpa (2011), while some additional modeling of the opt-out option (in our case no-purchase alternative) effects can be found in Hess and Rose (2008).

Formally, the utility function that individual, *n* obtains from choice alternative *j* in choice situation *t* is as follows:

(3)

$$U_{njt} = 1(I=1)\beta_1 * Nobuy + \beta_2 * PRICE_{njt} + \beta_3 OrgEU_{njt} + \beta_4 OrgBE_{njt} + \beta_5 AW_{njt} + \beta_6 FR_{njt} +$$

$$+ \beta_7 FRtrad + \beta_8 FRtot_{njt} + \beta_9 CO20_{njt} + \beta_{10} CO30_{njt} + 1_j(\eta_{nt}) + \varepsilon_{njt}$$

where $1_j(.)$ is an indicator function that takes the value of 1 for experimentally designed food profiles and η_{nt} is a zero-mean normally distributed respondent-specific idiosyncratic error component which is associated only with alternatives that portray a purchase decision, and is absent in the utility of the no purchase alternative (Scarpa, Willis, and Acutt 2007); ε_{njt} is the unobserved error term.

One of our main interests in this study lies in addressing whether: (1) accounting for ANA matters in terms of WTPs, and (2) monitoring stated ANA on the serial or choice task level leads to different WTP estimates (Hypothesis 1).To test these hypotheses, two steps were followed.

In the first step, we used the above utility specification to estimate two different models. The first model is a benchmark model where the full attended attributes are assumed (e.g. Full-Attendance)[3]. The second model, named "Standard-ANA" model, accounts for heterogeneity in respondent's ANA by restricting the parameters of self-reported ignored attributes to zero (Hensher, Rose, and Greene 2005; Campbell, Hutchanson, and Scarpa 2008).This model was estimated across both serial and choice task experiments. The implicit assumption of this model specification is that an observed choice provides no information concerning the respondent's preferences for these ignored attributes (Alemu et al. 2013). Hence, in the serial ANA experiment, the parameter estimates are conditional on the subset of those who claim that they considered the attributes (Campbell and Lorimer 2009). Similarly, in the choice task experiment, they are conditional on the subset of choice tasks in which the respondents claimed to have considered the attributes.

In the second step, the parameter estimates from both the "Full-Attendance" and the "Standard-ANA" models from serial (Standard-ANA serial) and choice task (Standard-ANA choice task) experiments were used to estimate the WTP estimates, which were used to test the following hypotheses:

$$H_{01}: (WTP_{Standard\ ANA\ Serial} - WTP_{Full-Attendance}) = 0 \text{ , and}$$

[3] We remind the reader that the full attendance behavior can only be investigated in the serial treatment data set since the respondents were not triggered by the ANA questions here as compared to in the choice task treatment. As such, the benchmark model is estimated only for this dataset.

$$H_{11}: (WTP_{Standard\ ANA\ Serial} - WTP_{Full-Attendance}) \neq 0$$

$$H_{02}: (WTP_{Standard\ ANA\ Choice\ Task} - WTP_{Full-Attendance}) = 0, \text{ and}$$

$$H_{12}: (WTP\ _{Standard\ ANA\ choice\ Task} - WTP_{Full-Attendance}) \neq 0$$

$$H_{03}: (WTP_{Standard\ ANA\ Serial}\ - WTP_{Standard\ ANA\ Choice\ Task}) = 0, \text{ and}$$

$$H_{13}: (WTP_{Standard\ ANA\ Serial}\ - WTP_{Standard\ ANA\ Choice\ Task}) \neq 0$$

If H_{01} and H_{02} are rejected then they confirm that accounting for ANA matters in terms of WTP estimates. If the If H_{03} is rejected it confirms that serial and choice task ANA produce different WTPs. This leads us into the second issue we wish to investigate; i.e., concerning which of the two stated ANA approaches (e.g. serial vs. choice task) is more meaningful in capturing the ANA behavior.

Validating stated ANA: Serial and Choice Task

If respondents truthfully report ANA statements, their choice behavior should be consistent with such self-reported ANA (Scarpa et al. 2013). To evaluate which one of the two stated ANA approaches (i.e., serial and choice task) best agrees with self-reported ANA statements, we applied the approach proposed by Hess and Hensher (2010) and estimated a second RPL-EC model, named "ANA – Validation", in which two coefficients are estimated for each of the attributes, depending on whether the attribute was stated as being either considered or ignored (Campbell, and Lorimer, 2009; Hess, and Hensher 2010; Alemu et al. 2013; Scarpa et al. 2013). This approach provides a more flexible alternative to the stringent restriction of the standard approach as respondents' actual attribute processing strategy may differ from the attribute processing strategy they stated to have adopted. As such, the utility function is as follows:

(4)

$$U_{njt} = 1_{nk}(I=1)[\beta_1^1 * PRICE_{njt} + \beta_2^1 OrgEU_{njt} + \beta_3^1 OrgBE_{njt} + \beta_4^1 AW_{njt} + +\beta_5^1 FR_{njt} + +\beta_6^1 FRtrad_{njt} +$$

$$+\beta_7^1 FRtot_{njt} + \beta_8^1 CO20_{njt} + \beta_9^1 CO30_{njt}] + 1_{nk}(I=0)[\beta_1^0 * PRICE_{njt} + \beta_2^0 OrgEU_{njt} + \beta_3^0 OrgBE_{njt} +$$

$$+\beta_4^0 AW_{njt} + \beta_5^0 FR_{njt} + \beta_6^0 FRtrad_{njt} + \beta_7^0 FRtot_{njt} + \beta_8^0 CO20_{njt} + \beta_9^0 CO30_{njt}] + \alpha_1 * Nobuy + 1_j(\eta_{nt})) + \varepsilon_{njt}$$

where 1_{nk} (·) is an indicator of ANA for respondent n and attribute k, with I=1 if respondent n stated to have attended to attribute k and I=0 otherwise. Accordingly, the utility coefficients β_k^1 refer to the parameters estimated for attended attributes, while the β_k^0 refer to those for the self-reported ignored attributes.

The significance of the parameter estimates for the ignored attributes can be used as a validation method (Scarpa et al 2013). If the coefficient estimates for the attributes they stated to have ignored are different from zero, then this would indicate that they did not fully ignore these attributes. If this condition is verified, then there is evidence of discrepancies between what survey respondents say they did and what they actually did (Campbell and Lorimer 2009). Hence, this model also allows us to corroborate whether or not the hypothesis of the standard method, which restricts the parameters to zero for the self-reported ignored attributes (Standard-ANA model), is appropriate in our data. We explore this in both the serial and choice task experiments. As pointed out by Campbell and Lorimer (2009), Hess and Hensher (2010), and Scarpa et al. (2013), if the coefficient estimates for the self-reported ignored attributes are significantly different from zero, then they ought to be closer to zero than the coefficient estimates of the considered attributes. This would also indicate that respondents did not fully ignore these attributes, and most likely just gave a lower importance to them as compared to the attributes they stated to have considered.

Inference of ANA using the equality constrained latent class model

Finally, to achieve the last objective of this study (i.e., comparing stated and inferred ANA approaches), we estimated the equality constrained latent class (ECLC) models for panel data

(Hess and Rose 2008; Scarpa et a. 2009; Campbell, Hensher, and Scarpa 2011; Caputo, Nayga, and Scarpa 2013). The ECLC models are different from standard latent class models intended to explore preference heterogeneity because they are based on classes embedding different forms of attendance to attributes during the panel of observed choices (Scarpa et al. 2013). In particular, selected attribute coefficients are constrained to zero in ANA classes to impose consistence with the notion that those attributes have been ignored during serial choice (Scarpa et al. 2009). Formally, in the ECLC model, the unconditional probability of the observed panel of choices is a weighted average over the *k* classes with weight π_k

$$(5)\quad \mathrm{P}_{n\mathbf{i}} = \sum_k \pi_k \prod_{t=1}^{T} \left[\frac{e^{\boldsymbol{\beta}_k^{'} \mathbf{x}_{kit}}}{\sum_j e^{\boldsymbol{\beta}_k^{'} \mathbf{x}_{kjt}}} \right]$$

In this application, two different ECLC models were specified. The first one is named LC 1+ 6 ANA and the second one is named LC 2 + 6 ANA. The LC 1+ 6 allows participants to belong to a certain latent class with a zero coefficient for certain attributes, while non-zero coefficients are assumed to be the same across the classes (Scarpa et al. 2009; 2013). As such, what is different across classes is the mixture of attributes in the indirect utility function that have coefficients constrained to be equal to zero, which implies zero weight of selected indirect utility attributes, as a consequence of non-attendance. Utility coefficients that are freely estimated are constrained to be equal across classes. Therefore, classes differ on the basis of the particular pattern of zero-valued coefficients, but do not differ in terms of taste intensities (e.g. only one preference class), thereby ignoring preference heterogeneity.

Given five attributes, a total of 32 possible class combinations are possible. In our case seven classes are specified for the LC 1+6: one full attendance (complete attendance class - AA), one complete ANA (ANA - random choice), and five classes for the lexicographic preferences (one for each lexicographic attribute preference hypothesized; only one out *k* matters, and all other $k-1$ not-attended to, and so constrained to zero). As such, a total of seven classes were obtained.

The LC 2 + 6 ANA accounts for the presence of separate classes of taste intensity as well as various patterns of serial attribute non-attendance (Caputo, Nayga, and Scarpa 2013). Accordingly, in this model the classes differ between each other for either (*a*) having different values of taste intensities β or for (*b*) having different sub-sets of attribute coefficients set to zero in accordance with different forms of attribute non-attendance. This is motivated by the fact that groups may differ not only in terms of patterns of attendance, but also in terms of taste intensities as demonstrated by the popularity of conventional latent class models, which were originally motivated by preference variation. For this model, two preference classes were specified. Preference class 1, which includes one full attendance complete attendance (complete attendance class - AA) and 5 lexicographic preferences, one for each attribute. Preference class two, incorporates one complete attendance class (full attendance class – AA) and one complete ANA (ANA - random choice). As a result, a total of 8 classes were obtained (2 + 1 + 5 =8) were obtained.

The exact combinations of taste-differing classes and sub-sets of non-attendance are defined with an iterative specification search which is guided by the usual information criteria for non-nested models: the Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC) and the modified Akaike Information Criteria (3AIC).

The WTP from the ECLC is derived by weighting by the class membership probability π_k the marginal WTP of each class k obtained from the usual ratio between attribute coefficient and cost coefficient (Caputo, Nayga, and Scarpa 2013; Scarpa et al. 2009).

Results

Sample

Data were collected by a market research company through an online survey in Belgium in March 2012 targeting the person of the household most often responsible for food purchasing. A total of 601 participants completed the CE surveys and they were randomly assigned to either Experiment 1 (serial ANA, N=344) or Experiment 2 (choice task ANA, N=257). A comparison of the socio-demographic distributions of the two CE experiments suggests that the sub-samples are similar in terms of their socio-demographic characteristics (chi-square $p>0.05$) (see supplementary material).

Stated ANA: Descriptive statistics

Turning to the self-reported ANA in the *Serial Experiment*, only 18% of the respondents reported to have attended all five attributes (see supplementary material, S3) and thus state to have made choices fully consistent with the continuity assumption. The remaining 82% of the respondents stated to have ignored at least one attribute, which shows that there is a non-negligible portion not attending to all the information given in the CE. The carbon footprint attribute was the most frequently ignored attribute (71%). Although the meaning of each attribute level was explained to the participants prior to the CE, the low awareness and non-existence of this carbon footprint label on the Belgian market might explain its low attendance. Also, as expected, the price attribute has the highest attendance and was reported to be ignored by only 26% of the respondents..

In the *Choice Task Experiment*, we recorded information about ANA for each of the eight choice tasks. In this experiment the carbon footprint attribute was ignored in 44% of all choice tasks and thus was the least attended attribute, while price had the highest attendance which is consistent to the *Serial Treatment*, Furthermore, almost 60% of the respondents attended to price in all eight choice tasks (0 times ignored) while the attendance for the sustainability label is lower with only 30 to 37% of respondents attending to it in all eight choice task. Additionally, that a large portion of respondents does not consistently ignore the same attributes across all choice tasks.

Approximately 32% (for price) to 70% (for carbon footprint) of respondents did not follow the same attribute processing behavior in all eight choice tasks and ignore the respective attributes 1 to 7 times, which thus indicates that collecting information on attribute processing behavior on the choice task level may be more informative than on the serial level where respondents are assumed to follow the same strategy for the whole sequence of choice tasks. This is consistent with findings in outdoor recreation (Scarpa, Thiene, and Hensher 2010), which indicates that the advantages of monitoring ANA at the choice task level.

Estimates from the full attendance and standard ANA RPL-EC models for Serial and Choice Task Experiments

The estimates of the "Standard ANA" model across both *Serial* and *Choice task Experiments*[4] are reported in table 3. The model allows for correlation across taste parameters using a Cholesky matrix (Cholesky matrix estimates are available upon request) in both Experiments.

We remind the readers that in the Standard ANA model the parameters of the ignored attributes are set to zero. As such, they are conditional for the subset of respondents who claimed to have attended the attributes at the sequence level (*Serial Experiment*) or choice task level *Choice Task Experiment*).

[4] In our choice models, preference differences may arise because of differences in the taste intensities and ANA behavior. However, some of these differences across CE treatments might be confounded by differences in the scale of the Gumbel error of the random utility. Accordingly, we tested for scale variation across serial and choice task treatments before proceeding with the data analysis. Following Hensher and Bradley (1993), Adamowicz et al. (1998), and Lusk, Roosen, and Fox (2003) the relative scale differences between the datasets from the two CE treatments (serial and choice task) were identified using an artificial nested logit tree structure, where a dataset represents a branch in the tree. The null-hypothesis of a difference in the scale was rejected.

As can be seen from table 3, the no-purchase options are statistically significant with a negative sign across both the serial and choice task experiments, indicating that respondents favor the proposed alternatives over the no-purchase option. Also, standard deviation of the error components (ERC) for both experiments are statistically significant, suggesting that heterogeneity across individuals with respect to their preference for the alternatives is an issue that needs to be modeled in these choice settings (Scarpa, Willis, and Acutt 2007). Finally, as expected, the price coefficients are negative and statistically significant at the 1% level.

Looking at the *Serial Experiment*, it can be noted that the coefficient estimates of all the sustainable labels are positive and statistically significant at the 1% level. Overall, results suggest that an increasing percentage of respondents are preferring chicken breast alternatives possessing a label bearing free range “total freedom” (*FRtot*), followed by “traditional free-range”(*FRtrad*) , the organic Belgium (*OrgBE*), the European organic (*OrgEU*), the “Free Range” (*FR*), the reduction of CO2 by 30% (*CO30*), the animal welfare (*AW*), and the reduction of CO2 by 20% (*CO20*) labels. Finally, there is heterogeneity in consumers’ preferences for sustainable food claims since the derived standard deviations of the coefficients of all the claims are statistically significant at the 1% level. Similar to the *Serial Experiment*, in the *Choice Task Experiment*, the coefficient estimates are positive and statistically significant at the 1% level, except for *CO20* which is statistically significant at the 5% level. Also, looking at the significance of the standard deviation, the heterogeneity of consumers’ preferences is confirmed, except for the FR label.

Tables 4 reports the marginal WTPs across *Serial* and *Choice Task Experiments* and the corresponding two-sided t-tests to verify the hypotheses with respect to the impact of ANA on the WTP estimates. By comparing the WTPs from the “Standard-ANA model” of the *Serial* and *Choice Task Experiments* with the WTPs obtained from the “Full-Attendance” model, it can be seen that our hypotheses ($H_{01}: WTP_{Standard\ ANA\ Serial} - WTP_{Full-Attendance} = 0$,and $H_{01}: WTP_{Standard\ ANA\ Serial} - WTP_{Full-Attendance} \neq 0$ for the serial Experiments; and

$H_{01}: WTP_{Standard\ ANA\ Choice\ Tsk} - WTP_{Full-Attendance} = 0$, and $H_{01}: WTP_{Standard\ ANA\ Choice\ task} - WTP_{Full-Attendance} \neq 0$ for the *Choice Task Experiment*) are rejected in 5 out of the 8 cases, signaling a decreases in WTPs when accounting for ANA at serial and choice task level. This evidence matches those observed in earlier studies (Campbell et al. 2008). On the other hand, the WTPs for the organic labels increase when accounting for both serial and choice task ANA, while for the AW label it increases for choice task and decrease for serial. As such, in accordance with Scarpa, Thiene, and Hensher (2010), the direction of the changes in WTPs when accounting for ANA remains an empirical issue.

Turning to the marginal conditional and unconditional WTPs across the *Serial* and *Choice Task Experiments* s, our second hypothesis ($H_{03}: WTP_{Standard\ ANA\ Serial} - WTP_{Standard\ ANA\ Choice\ Task} = 0$, and $H_{03}: WTP_{Standard\ ANA\ Serial} - WTP_{Standard\ ANA\ Choice\ Task} \neq 0$) is rejected in all of the analyzed labels, indicating that WTPs are affected by the level at which ANA information is collected (serial versus choice task), except for *FRtrad* label in the unconditional WTP. By comparing the magnitudes of the means of the unconditional WTP values across serial and choice task, it can noted respondents are willing to pay the highest price premium for *FRtot* (Euros 4.08 and 5.08 for the serial and choice task respectively) in both Experiments. However, the relative importance ranking of WTPs for the other labels changes across *Serial* and *Choice Task Experiments*. Specifically, in the serial Experiment, the relative importance ranking of marginal WTPs for the other labels is: *FRtrad* label, *FR*, *OrgBE*, *OrgEU*, *AW*, *CO30*, and *CO20*; while in the *Choice Task Experiment* the ranking is: *Org EU*,,*Org-BE*, *AW*, *FRtrad*, *FR*,*CO30*, and *CO20*.

Another important finding is that most of the WTP estimates in the *Choice Task Experiment* are higher than in the *Serial Experiment* for both conditional (5 out of 8) and unconditional (6 out of 8) WTPs. These findings do not support the ones by Scarpa, Thiene, Hensher (2010), who found increases in WTPs for ANA serial compared to choice task. However, the authors did not directly collect self-reported serial ANA information, but they reconstructed it from ANA information reported at the choice task level. Interestingly, while the difference in WTP estimates across the two experiments is considerably high in the case of the conditional WTP estimates across all labels, it is attenuated in the case of unconditional WTP estimates. However these changes are not monotonic. For example, when moving from *Serial* to *Choice Task Experiment* the relative change of the conditional WTP estimates for the *CO20* label is equal to 56 percent, while this difference goes down to 21 % in the unconditional WTPs. On the other hand, when moving from *Serial* to *Choice Task Experiment* the relative change of the conditional WTP estimates for the *FRtot* label decreases by 8.65 % cent but this goes up by 24.5% in the conditional WTPs.

Validity of ANA statements across serial and choice task

We now compare the concordance between the ANA statements across *Serial* and *Choice Task Experiments* using the approach proposed by Hess and Hensher 2010. Accordingly, we estimated separate parameters for those who attended and ignored the attributes (Table5). When estimated standard deviations were found to be insignificant, they were restricted to zero, implying fixed coefficients and an absence of heterogeneity.

Looking at the results for the *Serial Experiment*, we observe that the parameters estimated for those who said that they ignored the attributes are statistically different from zero except for the two organic labels (e.g. *OrgEU* and *OrgBE*). This is an important finding suggesting that respondents who stated to have ignored most of the attributes did not completely ignore them. As such for the *Serial treatment*, inconsistency exists between what people say they have ignored when asked at the serial level and what they really ignored. These results agree with the findings of other studies on serial ANA which used this modeling approach (Alemu et al. 2013; Campbell and Lorimer 2009), which found a discrepancy between what people said at the serial level and how they actually process attribute information. As such, this suggests that it might be inappropriate to model serial stated ANA using the standard approach, where zero values are assigned to the ignored coefficients. This is because, as pointed out by Carlsson, Kataria, and Lampi (2010), rather than ignoring attributes completely, respondents might be putting lower weights on attributes that they claimed to have ignored.

Interestingly, in the *Choice Task Experiment*, it can be noted that while the coefficients for the respondents who stated to attend the attributes are significantly different from zero, only two out of the nine coefficients belonging to the subset of respondents who claimed to ignore the attributes are statistically different than zero. These results suggest that the attribute processing strategy with respect to ANA reported by respondents at the choice task level is consistent with the strategy that they actually adopted. Hence, the standard ANA model, which constrained the ignored attributes to zero, seems to be suitable when using self-reported stated ANA information at the choice task level.

Overall, the parameter estimates from the ANA-Validation model suggest that while the use of the standard model is inappropriate in the case of serial ANA, it is suitable when using the choice task ANA data. This is because in the *Choice Task Experiment* there is little discrepancy between the self-stated ANA and the processing strategy picked up by the standard ANA model.

This difference in validation of the standard ANA model between the *Serial* and *Choice Task Experiment* can be explained by the considerable portion of respondents changing their attribute attendance behavior across choice sets (See supplementary material, table S3) which is capture in the *Choice Task Experiment* but not in the *Serial Experiment*. This is consistent with Puckett and Hensher (2009) who reported that ANA behavior may vary from choice task to choice task as respondents progress along the panel of choice situations allocated to each of them

As in Scarpa et al. (2013), we finally compared the parameters estimated for the subgroup who said they ignored the attributes with those stated to attend the attribute. A likelihood ratio test was used imposing the null hypothesis of identical parameters across the two subgroups (respondents who considered all the attributes and ignored the attributes). This was tested for the *Serial Experiment* as well as for the *Choice Task Experiment* For both experiments (*serial and choice task*), the null hypotheses were rejected with p-values smaller than 0.001 (Chi-square (15) =118.689 and Chi-square (19) =465). Hence, we conclude that informational content exists in the attendance statements across both serial and choice task levels.

Estimates of the ECLC models

Table 6 reports the estimates of the LC1 +6 ANA model. We remind the reader that this model has one preference class, which is composed by one full attendance class and 6 ANA classes. As can be seen, the top membership class is the complete –AA class, with the membership probability of 34%, followed by the random class (21%), and the lexicographic behavior based on price (AA-Price , 14.5%), only organic labels (AA-Org , 13.8%), only animal welfare label (AA-AW,5.8%), only free range labels (FREE , 5.7%), and only carbon footprint labels (AA-CO , 5.2%).

As mentioned earlier, respondents may differ not only in terms of ANA behavior, but also in terms of preference heterogeneity. As such, a second model, LC2 +6 ANA was estimated. Results are shown in table 7. The first preference class represents a membership probability of 60%, shared by six classes: complete AA (16%) followed by the lexicographic behavior based on organic labels (AA-Org , 12%), only free range labels (FREE , 8.9%), only by price (AA-Price , 8.7%), only carbon footprint labels (AA-CO , 7.5%), and only animal welfare label (AA-AW, 6.7%). The second preference class has difference preference structure across the analyzed labels and it account for a membership probability of 40%, which shared by a complete AA class (36%) and a random choice class (4%).Importantly, since both full attendance classes (complete AA) across both the two preferences classes report high membership probability, the LC2 +6 ANA model shows that respondents differ not only in terms of ANA patters but also in terms of taste intensity.

Comparing Serial ANA Choice task ANA, and Inferred ANA methods

The two stated ANA (e.g. serial and choice task) and the inferred ANA method are compared using two different approaches. The first approach refers to a comparison of the model fit across the different model specifications for the serial, choice task and inferred data. The second one uses the frequencies of ANA across the observed data (e.g. self-reported ANA for serial and choice task) and the inferred data to compare the concordance between these methods.

To compared the models fits across the two stated ANA along with the inferred methods, information criteria such as Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the modified Akaike Information Criteria (3AIC) are used; the lower the information criterion value, the better is the fit. Results are shown in table 8. First, looking at the performance of the Full-Attendance model and the Stated-ANA models (e.g. Standard-ANA and ANA-Validation), two main conclusion can be draw: (1) the model fit improves when accounting for ANA using both the two stated ANA (e.g. serial and choice task) compared to the model assuming full attendance behavior; (2) addressing for ANA issue using self-reported choice task ANA rather than self-reported serial task ANA results in a better model fit. Most important, for the *Choice Task Experiment*, the "Standard- ANA" model has the best performance which is consistent with earlier reported results. For the *Serial Experiment* on the other hand,, the ANA-Validation model is the best model. The differences in best model performances across *Serial* and *Choice Task Experiment* is also confirmed by the parameter estimates from the ANA-Validation model (Table 5), which shown that in the *Serial Experiment* respondents do not actually fully ignored the attributes that they have stated to ignore during the experiment and thus the standard ANA model may lead to biased results. By comparing the information criteria of the inferred ANA models, it can be noted that CL 2 + 6 model outperforms that CL 1 + 6. This might be due to the fact that it does not account for heterogeneity features between preference classes, which might plausible take place in consumer choice behavior when valuating sustainable labels.

Turning to the second approach used to compare the two stated ANA approaches (e.g. serial ANA and choice task ANA), with the inferred ANA method, we used the frequencies of self-reported ANA of both at serial and choice task experiment with the frequencies of ANA inferred by the two ECLC models (LC1 +6 ANA and LC2 +6 ANA). Results are reported in table 9. It can be noted that differences in ANA exist across the different approaches. Specifically, when comparing the self-stated ANA in the serial versus the LC1 +6 ANA, frequencies of ignorance are higher for most of the attributes. While, the frequencies of ignorance across attributes inferred thought the second latent class specification (LC2 +6 ANA) are more in accordance with the self-report ANA. Most important, the LC2 +6 ANA information are in concordance with the ones observed from the choice task ANA, except for the price.

Conclusion

Economists interested in market valuation study have been long concerned about how survey respondents' process attributes information. A large body of the literature has reported that respondents might ignore some of the described attributes while evaluating the alternatives in choice tasks. In CEs, this decision heuristic, referred to as "attribute non-attendance" (ANA), causes a bias in parameter estimates when not accounted for and may have a substantial effect on the marginal WTP estimates and welfare estimates (Campbell, Hutchinson, and Scarpa 2008; Hensher and Rose 2009; Carlsson, Kataria, and Lampi 2010), leading to over- or under-estimation of these values. Therefore, reliance on fully rational decision making in a choice context when modeling and predicting consumer preferences might be ill-advised. Hence, it is important to account for possible ANA behavior and understand the attribute processing strategies adopted by the respondents when making choices in a CE.

Accordingly, the present study was designed to (1) investigate whether or not ANA is an issue to take into account in food consumer valuation studies and (2) if so, which approach is the most suitable to capture ANA behavior in CE studies. As a practical application, we evaluate the serial and choice task ANA approaches and also compare these approaches to the inferred ANA method. Specifically, we carried out two different CEs. In the first one, ANA information was collected at the end of the sequence of the choice sets (*Serial Experiment*), while in the second one, the ANA statements were asked at the end of each choice task (*Choice Task Experiment*). The serial and choice task data were analyzed using a Random Parameter Logit models with error components (RPL-EC). Specifically, three model specifications were estimated. The first model is a conventional RPL-EC where full attendance is assumed. The second one pertains to the standard ANA model, where the self-reported ignored attributes are set to zero. The third model was used to validate the self reported ANA statements for both serial and choice task treatments. Finally, the two stated ANA methods were compared to the inferred approach, for which we used two specifications of an equally constrained latent class model (ECLC).

To our knowledge, our work is the first to investigate both the two stated ANA methods along with inferred ANA approach in a consumer food choice setting. Also, it is the first study that compares the two methods of collecting stated ANA information (serial versus choice task) using data directly collected at both the serial and choice task levels. Our findings generally suggest the following:

(a) ANA is also an issue in consumer food choice settings and is likely to impact WTP estimates. As such, ANA should be accounted for;

(b) The self-reported ANA information recorded at the choice task level suggests that few respondents follow the same attribute processing strategies throughout the entire sequence of choice tasks (eight choice tasks in our case). As such collecting ANA information at the serial level, and thus assuming that they follow one strategy throughout the whole sequence of choice tasks, is less suitable than collecting it at the choice task level as it fails to capture the changes in attribute processing behavior during the CE. This is also confirmed by the estimates obtained from the validation model (ANA- Validation) which shows that most of the coefficients of the self-reported ignored attributes in the *Serial Experiment* are statistically significant from zero. This means that the respondents who stated to have ignored these attributes throughout the whole sequence of the choice tasks did not completely do so. On the other hand, only a few coefficients are found to be significantly different from zero in the *Choice Task Experiment*. This signifies that there is less discrepancies between what respondents said they did and what they actually did when the ANA information was collected at the choice task level rather than at the serial level. This result corroborates the idea of Scarpa, Thiene, and Hensher (2009) that the intra-respondent variation of attribute attendance at the single choice task level is of substantial importance to the welfare estimates and model fit when addressing ANA behavior. Together with the finding mentioned earlier, our study also suggests that information on ANA collected at the single choice task level induces respondents to reveal their true ANA behavior.

(c) When accounting for ANA using the inferred approach, a model allowing for heterogeneity in terms of both preferences and ANA behavior better fits the data than a model that only assumes heterogeneity in ANA behavior.

Taken together, these findings suggest a number of recommendations in terms of CE survey designs and modeling approaches. They can also provide guidance to questions such as how one should collect ANA information and what model specifications should be used to incorporate ANA behavior in CE models.

First, since respondents could change its attribute processing rule during the CE, collecting self-stated ANA information at the choice task level is the most appropriate method to capture their true ANA behavior. As such, the use of the standard ANA model might be appropriate for choice task ANA. Second, when collecting self-reported serial ANA information, it is likely that there are more discrepancies between what people say they do and what they actually do in terms of ANA behavior. As such, the model proposed by Hess and Hensher (2010) seems to be the most appropriate one to use for serial ANA since it is able to capture the discrepancy between self-reported ANA information and predicted ANA behavior. Lastly, when one has CE data without self-reported ANA, it would be advisable to account for it using a latent class approach that accounts for heterogeneity across class preferences and ANA behavior.

There are a number of interesting areas on the issue of ANA that needs more attention. For example, future research on attribute processing strategies with respect to ANA should also look at non-attendance not just of an attribute but also in the levels of an attribute. People may follow certain attribute processing strategies based on the attribute level present in the choice task. This issue related to attribute level processing strategies was also suggested by Scarpa, Thiene, and Hensher (2010), who mentioned that the attendance may be triggered by the presence or absence of a certain attribute level or combinations of certain attribute levels in the presented alternatives.

While our models incorporated the stated ANA effects, we did not ask the respondents the reason why they ignored an attribute. This could be valuable information that can be incorporated into the model. While the reasons for ANA have been studied for serial ANA (Alemu et al. 2013), no study has incorporated the reasons for ANA at the choice task level. Future research should also investigate how the ANA is linked to the complexity of the task (e.g., number of attributes, number of attribute levels, number of choice sets, ranges of attributes) (Hensher 2006; Carlsson, Kataria, and Lampi 2010), the importance and relevance of the attributes, and the relevance of the attribute levels (Hensher, Rose, and Greene 2012). Hensher, Rose, and Greene (2012) also suggests the need for research on the use of respondent-specific attribute ranges as certain attributes might only be relevant if a respondent-specific threshold level is reached.

All of these issues related to ANA and our new findings in this paper have important implications for the interpretation of WTP estimates from a food and agribusiness perspective and hence, in the development of marketing strategies based on such estimates. Those who are responsible for the design of such strategies should be aware of the methodological issues and how these could affect the valuation estimates. Otherwise, the developed strategies risk tobe ineffective since they could be based on unrealistic or inaccurate market information.

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Table 1. Attributes and levels for the choice experiment

Attributes	Levels considered
Organic label	- No organic label - Biogarantie label (OrgBE) - EU Organic label (OrgEU)
Animal welfare protection label	- No animal welfare label present - European Animal welfare label (AW)
Types of free-range farming claim	- No free range claim - Free range (FR) - Traditional free-range (FRtrad) - Free range-total freedom (FRtot)
Reduced carbon footprint label (CO_2 emitted)	- No carbon footprint label - 20% reduction: 5.6 kg CO_2e compared to 7 kg CO_2 (CO2) - 30% reduction: 4.9 kg CO_2e compared to 7 kg CO_2 (CO3)
Price	- €10/kg - €15/kg - €20/kg - €25/kg

Table 2. Attributes ignored by the respondents in choice task Experiment (N respondents=257)

	% Respondents ignoring the attribute k times								
k	0	1	2	3	4	5	6	7	8
ORG	34.6	10.1	10.9	3.5	3.1	3.9	2.3	5.8	25.7
AW	36.6	10.5	7.4	6.2	5.8	3.1	2.7	4.3	23.3
FREE	40.1	15.6	7.4	4.7	4.7	1.6	2.7	4.3	19.1
CO	30.0	8.9	7.0	5.1	4.3	2.7	9.3	32.7	0.0
Price	58.8	13.2	5.1	3.9	3.1	1.9	0.8	4.3	8.9

Table 3: Standard ANA model across Serial and Choice Task Treatments and Full attendance model

	Serial Treatment (N=2752)				Choice Task (N=2056)				Full Attendance (N=2752)			
	β	t-test	σ	t-test	β	t-test	σ	t-test	β	t-test	σ	t-test
No-buy	-7.63	12.84	-	-	-6.78	9.84	-	-	-6.82	11.53	–	-
Sd. of ERC			7.05	18.60			6.99	11.54	-	-	5.58	10.91
Subsets of respondents Considered												
Price	-0.29	18.37	-	-	-0.30	14.31			-0.25	14.81	-	-
OrgEU	1.48	6.44	1.87	7.25	2.44	7.74	1.92	5.27	0.23	1.21	2.53	10.30
OrgBE	1.7	8.95	1.36	6.57	1.92	7.18	1.99	6.55	0.67	4.77	1.48	8.63
AW	1.08	8.25	0.7	3.65	1.80	9.27	1.20	3.73	0.86	7.06	1.10	8.43
FR	1.47	7.51	1.17	4.45	1.41	6.21	0.94	1.40	1.41	7.39	1.20	1.33
FRtrad	1.72	8.29	1.02	3.01	1.59	6.18	1.17	1.96	1.63	8.08	0.67	2.95
FRtot	2.01	9	1.7	5.67	2.33	8.17	1.57	2.70	2.03	9.34	1.67	5.99
CO20	0.99	4.18	1.35	4.90	0.45	2.43	1.09	3.05	0.50	3.95	1.34	7.57
CO30	1.38	4.47	2.21	5.51	1.13	4.19	1.57	3.21	0.75	4.69	1.81	7.93

Ignored

Price	0	Fixed	0	Fixed
OrgEU	0	Fixed	0	Fixed
OrgBE	0	Fixed	0	Fixed
AW	0	Fixed	0	Fixed
FR	0	Fixed	0	Fixed
FRtrad	0	Fixed	0	Fixed
FRtot	0	Fixed	0	Fixed
CO20	0	Fixed	0	Fixed
CO30	0	Fixed	0	Fixed

Table4: WTP Estimates from the Standard ANA model across Serial and Choice Task Treatments and from the Full Attendance Model

	Serial Treatment		Choice Task Treatment		Full-Attendance	
WTP[a]	Mean (st. err)	% of respondents	Mean (st. err)	% of choice task	Mean (st. err)	% of Respondents
Conditional WTPs						
OrgEU	5.17 (0.77)	50	8.03 (1.00)	58		
OrgBE	5.96 (0.63)	50	6.32 (0.85)	58		
AW	3.78 (0.46)	51	5.91 (0.63)	61		
FR	5.16 (0.68)	58	4.62 (0.76)	66		
FRtrad	6.04 (0.71)	58	5.21 (0.84)	66		
FRtot	7.05 (0.75)	58	7.66 (0.88)	66		
CO20	3.46 (0.81)	29	1.46 (0.60)	56		
CO30	4.83 (1.06)	29	3.70 (0.86)	56		
Unconditional WTPs[b]						
OrgEU	2.57 (0.38)	100	4.67 (0.58)	100	0.92 (0.76)	100
OrgBE	2.96[b] (0.31)	100	3.68 (0.49)	100	2.62[b] (0.53)	100
AW	1.91 (0.23)	100	3.58[c] (0.38)	100	3.38[c] (0.45)	100
FR	2.99 (0.39)	100	3.06 (0.50)	100	5.56 (0.71)	100
FRtrad	3.49[a] (0.41)	100	3.45[a] (0.56)	100	6.42 (0.70)	100
FRtot	4.08 (0.43)	100	5.08 (0.58)	100	7.99 (0.71)	100
CO20	1.02 (0.24)	100	0.81 (0.33)	100	1.95 (0.48)	100
CO30	1.42 (0.31)	100	2.06 (0.48)	100	2.95 (0.59)	100

[a] For the WTP calculations, we assume that the price coefficient for those ignoring price is the same as those considered price

[b]The unconditional WTP averages is a weighted average based on the processing strategies adopted by respondents. This included the WTP of zero for those stating to have ignored the attribute.

Values with the same letter as subscript indicate that they are not significantly different

Table 5: Estimates from the Validation ANA model across Serial and Choice Task Treatments

	Serial Treatment				Choice Task Treatment			
	β	t-test	σ	t-test	β	t-test	σ	t-test
No-buy	-6.81	12.38			-7.54	10.03		
Sd. of ERC			5.62	11.69			7.41	13.32
Considered								
Price	-0.25	19.71	Fixed	Fixed	-0.32	14.26	Fixed	Fixed
OrgEU	1.02	7.37	Fixed	Fixed	2.64	8.08	2.18	5.74
OrgBE	1.20	10.42	0.26	1.76	2.05	7.24	2.23	6.54
AW	0.88	8.94	0.50	3.63	1.92	8.64	1.49	6.41
FR	0.95	7.18	Fixed	Fixed	1.85	6.40	1.59	4.31
FRtrad	1.24	8.05	Fixed	Fixed	1.98	6.25	1.98	5.13
FRtot	1.65	9.86	0.96	2.50	2.80	8.35	2.17	6.03
CO20	0.62	3.69	0.90	3.61	0.65	2.81	1.86	5.98
CO30	1.19	4.88	1.54	3.75	1.13	3.74	2.05	5.14
Ignored								
Price	-0.05	4.18	Fixed	Fixed	-0.08	3.66	Fixed	Fixed
OrgEU	-0.05	0.41	Fixed	Fixed	-0.33	1.39	0.83	2.64
OrgBE	-0.08	0.83	Fixed	Fixed	-0.40	2.45	Fixed	Fixed
AW	4.20	2.51	Fixed	Fixed	-0.07	0.51	Fixed	Fixed
FR	0.30	2.19	Fixed	Fixed	0.13	0.56	Fixed	Fixed
FRtrad	2.34	2.13	Fixed	Fixed	0.07	0.27	Fixed	Fixed
FRtot	0.47	3.22	Fixed	Fixed	0.21	0.89	Fixed	Fixed
CO20	0.16	2.70	Fixed	Fixed	0.13	0.73	Fixed	Fixed
CO30	0.43	4.05	Fixed	Fixed	-0.05	0.26	Fixed	Fixed

Table 6. Estimates from the LC 1 + 6 ANA Model

Attendance classes[1]		Full-AA	Random	AA-Price	AA-Org	AA-AW	AA-FREE	AA-CO
Class probabilities		34.2%	20.8%	14.5%	13.8%	5.8%	5.7%	20.8%
No_buy (β_0)	Means	-11.35	0(Fixed)	-11.35	-11.35	-11.35	-11.35	-11.35
	T-test	8.58		8.58	8.58	8.58	8.58	8.58
Price	Means	-0.66	0(Fixed)	-0.66	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)
	T-test	10.06	0(Fixed)	10.06	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)
OrgEU	Means	1.10	0(Fixed)	0(Fixed)	1.10	0(Fixed)	0(Fixed)	0(Fixed)
	T-test	3.46	0(Fixed)	0(Fixed)	3.46	0(Fixed)	0(Fixed)	0(Fixed)
OrgBE	Means	1.37	0(Fixed)	0(Fixed)	1.37	0(Fixed)	0(Fixed)	0(Fixed)
	T-test	6.68	0(Fixed)	0(Fixed)	6.68	0(Fixed)	0(Fixed)	0(Fixed)
AW	Means	1.30	0(Fixed)	0(Fixed)	0(Fixed)	1.30	0(Fixed)	0(Fixed)
	T-test	6.47	0(Fixed)	0(Fixed)	0(Fixed)	6.47	0(Fixed)	0(Fixed)
FR	Means	1.67	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	1.67	0(Fixed)
	T-test	6.00	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	6.00	0(Fixed)
FRtrad	Means	2.10	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	2.10	0(Fixed)
	T-test	6.38	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	6.38	0(Fixed)

FRtot	Means	3.43	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	3.43	0(Fixed)
	T-test	8.61	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	8.61	0(Fixed)
CO20	Means	0.88	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	0.88
	T-test	4.17	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	4.17
CO30	Means	2.13	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	2.13
	T-test	6.16	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	6.16
AIC3/N					1.438			

[1] Full-AA means full attendance class; Random means complete ANA; AA-Price, AA-Org, AA-AW, AA-FREE, AA-CO C mean that only one out k attribut*es* matters, and all other $k-1$ not-attended to, and so constrained to zero.

Table 7: Estimates of the LC2+6ANA

		Preference class 1						Preference class 2	
Attendance classes[1]		Full-AA1	AA-Price	AA-Org	AA-AW	AA-FR	AA-CO2	Full-AA2	Random
Class probabilities		16.0%	8.7%	12.0%	6.7%	8.9%	7.5%	35.5	4.6
No_buy	Means	-2.30	-2.30	-2.30	-2.30	-2.30	-2.30	-14.05	0(Fixed)
	T-test	10.11	10.11	10.11	10.11	10.11	10.11	13.98	
Price	Means	-0.34	-0.34	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	-0.61	0(Fixed)
	T-test	16.67	16.67	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)		0(Fixed)
OrgEU	Means	1.78	0(Fixed)	1.78	0(Fixed)	0(Fixed)	0(Fixed)	-0.87	0(Fixed)
	T-test	8.14	0(Fixed)	8.14	0(Fixed)	0(Fixed)	0(Fixed)	1.95	0(Fixed)
OrgBE	Means	1.67)	0(Fixed)	1.67	0(Fixed)	0(Fixed)	0(Fixed)	0.40	0(Fixed)
	T-test	8.32	0(Fixed)	8.32	0(Fixed)	0(Fixed)	0(Fixed)	1.07	0(Fixed)
AW	Means	1.25	0(Fixed)	0(Fixed)	1.25	0(Fixed)	0(Fixed)	0.56	0(Fixed)
	T-test	6.32	0(Fixed)	0(Fixed)	6.32	0(Fixed)	0(Fixed)	2.57	0(Fixed)
FR	Means	1.58	0(Fixed)	0(Fixed)	0(Fixed)	1.58	0(Fixed)	1.38	0(Fixed)
	T-test	6.98	0(Fixed)	0(Fixed)	0(Fixed)	6.98	0(Fixed)	2.60	0(Fixed)
FRtrad	Means	2.19	0(Fixed)	0(Fixed)	0(Fixed)	2.19	0(Fixed)	1.51	0(Fixed)
	T-test	7.43	0(Fixed)	0(Fixed)	0(Fixed)	7.43	0(Fixed)	2.11	0(Fixed)
FRtot	Means	2.74	0(Fixed)	0(Fixed)	0(Fixed)	2.74	0(Fixed)	1.66	0(Fixed)

	T-test	7.75	0(Fixed)	0(Fixed)	0(Fixed)	7.75	0(Fixed)	2.25	0(Fixed)
CO20	Means	0.79	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	0.79	0.15	0(Fixed)
	T-test	3.21	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	3.21	0.48	0(Fixed)
CO30	Means	1.24	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	1.24	0.99	0(Fixed)
	T-test	4.37	0(Fixed)	0(Fixed)	0(Fixed)	0(Fixed)	4.37	2.07	0(Fixed)

[1]Full-AA means full attendance class; Random means complete ANA; AA-Price, AA-Org, AA-AW, AA-FREE, AA-CO C mean that only one out k attribut*es* matters, and all other $k - 1$ not-attended to, and so constrained to zero.

Table 8: Summary statistics of model fit

	Full Attendance	Serial ANA		Choice task ANA		ECLC	
		Standard ANA	ANA Validation	Standard ANA	ANA Validation	CL 1+6 ANA	CL 2+6 ANA
N	2752	2752	2752	2056	2056	2752	2752
LL	-1780.14	-1712.88	-1720.8	-1126.17	-1108.77	-1954.37	-1781.33
BIC/N	1.452	1.403	1.366	1.300	1.353	1.466	1.372
AIC/N	1.334	1.285	1.280	1.149	1.151	1.432	1.314
AIC3/N	1.354	1.305	1.294	1.176	1.187	1.438	1.324
N. param.	55	55	40	55	74	16	27

Table 9: Frequencies of ANA self-reported (serial and choice task) versus inferred ANA latent class (ELCL).

	Serial treatment	Choice Task treatment			Latent class	
	% Respondents	% Choice tasks	% Respondents ignoring in all eight choice tasks	% ignoring in 1 to 7 choice sets	LC1+6ANA	LC2+6ANA
ORG	50.29	41.83	25.68	39.69	51.92	36.4
AW	49.42	39.49	23.35	40.08	59.99	41.7
FR	42.15	33.71	19.07	40.86	60.07	39.5
CO_2	70.64	44.21	0.00	70.04	60.58	40.9
Price	25.58	20.43	8.95	32.30	51.25	39.7
N	344[1]	2056	257[1]	257[1]	344[1]	344

[1] Number of Respondents.

[2] Number of total choices (e.g. 8 per respondents).

Supplementary material

S1. Demographics across treatments

Demographics	**Treatment 1 (%)**	**Treatment 2 (%)**	**p-value - Chi-squared test**
Gender			**0.591**
Male	40	37	
Female	60	63	
Age group			0.364
18-24 years	12	15	
25-34 years	24	24	
35-44 years	15	15	
45-54 years	27	24	
55-64 years	18	14	
65 years or older	4	8	
Living situation			**0.634**
Alone	14	15	
With others	86	85	
Household members of 15 years and older			**0.412**
1	14	15	
2	51	50	
3	16	13	
4	14	14	
≥ 5	5	8	
Children younger than 15 years			**0.801**
0	77	78	
1	10	9	
2	10	9	
≥3	3	4	
Educational level completed			**0.437**
Elementary school or high school	27	23	
Higher education (not university)	43	44	

University	30	33	
Occupation			**0.418**
Full-time employed	62	62	
Part-time employed	12	10	
Retired	9	11	
Student	9	13	
Unemployed (seeking work)	3	2	
Houseman/housewife	5	2	
Financial situation			**0.232**
Difficult	13	11	
Moderate	37	33	
Moderate to well-off	50	57	

TableS2. Follow-up question on attribute attendance

Have you ignored any of the attributes? If yes, which of the following attributes did you ignore?
Information about the organic label
Information about the type free-range farming
Information about the carbon footprint label
Information about
Information about the price

Table S3.Number and Attributes Ignored by the respondents in Experiment 1

Number of attributes ignored	% Respondents
0	17.73
1	16.57
2	16.86
3	15.12
4	26.16
5	7.56

Table S4 Number of attribute ignored across choice tasks in Experiment 2

Number of attribute ignored (% Respondents)								
	Ch1[1]	**Ch2**	**Ch3**	**Ch4**	**Ch5**	**Ch6**	**Ch7**	**Ch8**
0	19.07	26.46	35.02	34.63	29.18	33.46	43.97	38.13
1	21.40	19.84	16.73	16.73	15.56	11.28	14.79	15.18
2	23.74	12.84	12.06	12.06	12.45	12.84	7.0	12.06
3	13.23	15.18	11.67	10.89	15.56	13.62	8.56	8.56
4	17.51	19.84	18.68	19.84	21.40	23.35	19.07	20.23
5	5.06	5.84	6.23	5.84	5.84	5.45	6.61	5.84

[1] Choice tasks