Investigating attribute non-attendance effects in conjoint analysis methods performance: Choice experiment, ranking conjoint analysis and best worst scaling.

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Abstract:

This paper addresses a set of methodological questions. First, it assesses the variation of the level of ANA in different non-hypothetical CA formats. Second, it explores whether asking respondents to report the attributes they ignored after each choice set or at the end of the choice task yield comparable results. Lastly, it explores the implications of taking into account ANA information on respondents' willingness to pay and on the external predictive powers of the estimated parameters. To answer these research questions, three treatments were carried out, non-hypothetical CE (NHCE), non-hypothetical RCA (NHRCA) and non-hypothetical BWS (NHBWS). The results reveal that taking into account ANA information significantly improved the goodness-of-fit of the estimated models, especially when full ranking information is considered as NHRCA and NHBWS. In term of marginal WTP estimates, the results show neither of the two ANA approaches appears to be a clear winner. Also, our results show that taken into account ANA information not seem to improve significantly the predictive power of estimated parameters.

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Introduction

Since its introduction conjoint analysis (CA) has become one of the most popular research tools to elicit consumer's preferences and willingness to pay (WTP). It is a stated preference method that involves human participant to rate, rank or choose between competing products concepts or alternatives, such as choice experiment (CE); ranking conjoint analysis (RCA), and best worst scaling (BWS). CA has been frequently used in different disciplines such as marketing (Chang et al., 2009; Dong et al., 2010), agriculture economics (Corrigan et al., 2009; Menapace et al., 2011), environmental economics (Campbell and Lorimer, 2009; Scarpa et al., 2011), transport (Louviere et al., 2008; Greene and hensher, 2013), and health economics (De Bekker et al., 2012; Lancsar et al., 2013).

CA gained popularity thanks to its ability to mimic real market settings where consumers are offered competing products and have the opportunity to choose the product that fits most their preferences. However, several papers (Hensher et al., 2005; Campbell et al., 2008; Campbell and Lorimer, 2009; Hensher and Greene, 2010; Carlsson et al., 2010; Hole 2011a) have found evidence that a sub-set of respondents in CA are not considering all the attributes when making their choices. In fact, respondents sometimes appear to ignore one or several attributes. This respondent behaviour is termed as attribute non-attendance (ANA). The complexity of the choice task (DeShazo and Fermo, 2004; Hensher, 2006), attribute irrelevance (Campbell et al., 2008; Puckett and Hensher, 2008) and the hypothetical nature of the choice task (Collins et al., 2013; Hess et al., 2013) have been mentioned in the literature as the main reasons behind ANA.

There is a growing number of evidence suggesting that ANA may lead to biased coefficient estimates and model performance, if it is not corrected for when the data is being analyzed (Hensher and Rose, 2009; Scarpa et al., 2010; Campbell et al., 2011; Mariel et al., 2013). The analysis of CA data is based on the theory of consumer behavior (Lancaster, 1966; McFadden, 1974) and assumes continuous preferences and thus unlimited substitutability between the attributes considered (Hoyos, 2010). This axiom of respondents' preferences continuity implies that all respondents, in their decision and when choosing their most preferred product concept, take into account all of the proposed attributes as well as the trade-offs between them (Hensher et al., 2005). Therefore, when a participant not take into consideration all the attributes presented and ignores one of them for example, it suggest that

there will be no trade-off between the ignored attribute and another attribute. Hence, it suggests that there is no marginal rate of substitution that can be calculated at individual level, which resultant estimated parameters and willingness-to-pay (WTP) estimates are biased and could be affect the model performance (Hoyos, 2010).

Two main approaches have been suggested to address the problem ANA. First, the stated attribute non-attendance (S-ANA) approach (Hensher et al., 2005; Kehlbacher et al., 2013; Alemu et al., 2013) in which respondents are asked directly whether they have ignored one or more attributes describing the alternatives while choosing among them. Second, the analytical attribute non-attendance (A-ANA) approach (Campbell et al., 2011; Lagarde, 2013; scarpa et al., 2013) which, contrary to the former, does not involve self-reported responses but consists in defining rules for recognizing ANA. In the literature, the debate about which of these two approaches is best at identifying ANA behaviour has gained high attention. Hensher and Rose (2009) commented that main inconvenient of S-ANA approach based of self reported measures which raise concerns about reliability of participants' responses. For example, responses could be influenced by how the question is asked or how the question it is interpreted. Another inconvenient of S-ANA could be the additional cost in terms of survey duration of asking these supplementary questions.

However, Scarpa et al. (2013) concluded that the stated and inferred approaches yield comparable results when addressing the problem of ANA. Mariel et al. (2013) revealed that the analytical approach does not seem to correctly predict actual ANA, at choice task level. Furthermore, Hoyos et al. (2010) show that the S-ANA approach may be more appropriate than A-ANA approach, based on simulation experiments. Therefore, is no general consensus on exactly how attribute non-attendance should be dealt with. In the literature and into another debate, recent studies have shown that if attribute non-attendance information is collected at the end of the entire choice treatments (serial S-ANA), it may be difficult for the respondents to answer because they may be applied different attribute processing strategies for different choice tasks (Puckett and Hensher, 2009; Caputo et al., 2014).

To the best of our knowledge, few studies have examined the ANA in food choice study (Scarpa et al., 2013; and Bello and Abdulai, 2016; Caputo et al., 2017). Additionally, except of Caputo et al. (2017), no other known study have examined the ANA information at both the serial and choice task levels in consumer food choice. Furthermore, while some studies assessed the comparability of different CA response formats in terms of respondents WTP, internal and external validity, and model performance (Caparrós et al., 2008; Chang et al., 2009; Akaichi et al., 2013), to our knowledge, none study has taken into account the effect of

cognitive effort spent by respondents in the different CA responses formats when assessing ANA information. Additionally, despite the wide application of ANA approaches in other fields such as environmental, transportation, and heath economics fields, none study compared the performance ANA approaches (Both stated and inferred approaches) in terms of predictive power of the estimated parameters.

To overcome previous papers' shortcomings, this paper significantly contributes to the literature on ANA by addressing the following research questions:

- Assessing the variation of the level of ANA in different non-hypothetical CA formats: choice experiments (CE), Ranking Conjoint Analysis (RCA) and Best-Worst Scaling (BWS).
- Assessing whether asking respondents to report the attributes they ignored after each choice set or at the end of the choice task yield comparable results.
- Assessing the implications of taking into account the collected information on ANA on respondents' willingness to pay and on the external predictive powers of the estimated parameters.
- Validating of self reported ANA behaviour deduced from the alternative ways of modelling stated ANA serial and choice task level and exploring the concordance of the last methods with the inferred method across the three CA methods studied[1].

This article is structured into five sections. The next section reports the experimental procedures we used to set up the serial and the choice task in the different CA responses formats. This is then followed by section that describes the econometric models used. The results are presented and discussed in the fourth section. In the fifth section, we conclude.

Experimental Procedures

To answer these research questions, three treatments were carried out, non-hypothetical CE (NHCE), non-hypothetical RCA (NHRCA) and non-hypothetical BWS (NHBWS). To assess the differences between these treatments a sample of 165 Barcelona' citizens was recruited to evaluate their preferences towards the purchase of olive oil. The participants were randomly and equally distributed over the different treatments[2]. The main attributes and attribute levels were first identified from literature review and two focus groups carried out among highly experienced and low experienced olive oil consumers. Four attributes were

[1] Regrettably, in view of time constraints, the results of the last research question will be included in the full version if the paper gets accepted in the conference.

[2] The participants were randomly recruited. Across the treatments, no significant differences at the 5% level were found in relation to gender and age. However, significant differences were found in terms of education level and self-reported income levels.

selected, three with three levels: type of olive oil (virgin extra, virgin, and refined olive oil)[3], origin (Andalucía, Catalonia, and rest of Spain) and price (2.20 €/liter, 3.50 €/liter, and 4.80 €/liter, which account for 85% of the price distribution in retail outlets), and one with two levels: brand (Manufacturer brand and private brand).

The combination of attribute levels generates a total of 54 (3^3*2) one liter bottles of olive oil. Following the Street and Burgess (2007), an orthogonal fractional factorial design, taking into account only main effects, was generated to reduce the number of combinations, resulting in 9 choice products, which will be considered as the first option in each choice set. Four additional options were offered to respondents in each choice set (plus the no choice option) applying the following generators (1000), (1111), (2121), and (2122) on the orthogonal design obtained. This resulted in a 100% efficient design.

During each treatment, the participants did two main tasks. The first task consists of the main of either treatments (NHCE, NHRCA or NHBWS). Respondents were offered 10 choice sets one by one (9 choice sets from the experimental design plus the fifth card which was presented at the end to assess the consistency). In each choice set, the participant was asked to choice their preferred option or to rank the options based on their preferences, that is, taking into account their real purchase habits. The second task, named the holdout task, was carried out to determine the external validity of the estimated parameters obtained from the different elicitation methods. The holdout task is a choice exercise in nature in which each participant had to choose just one product from a choice set including 10 alternatives generated from the full factorial design and different to those used in the first task. Each treatment of the experiment was conducted over 5 sessions throughout both different days of the week and different hours of day. Each session includes a maximum of 10-15 persons. After the two tasks, the participants fulfilled a short questionnaire aimed at collecting socio-demographic and lexicographic characteristics of respondents as well as on attitudes and olive purchasing and consumption habits.

At the beginning of the experiment, participants were informed that they would receive 15 Euros in cash at the end of the experiment. Additionally, we explained them the functional mechanism of the assigned treatment. In the next section details about the experimental procedure of each treatment are presented.

[3] The three types of olive oil were defined according to the International Olive Council (IOC). In this context, the refined olive oil is defined as the olive oil obtained from virgin olive oils by refining methods which do not lead to alterations. This are marketed as "olive oil". Respondents were aware about differences across levels.

Hypothetical (HCE) and non-hypothetical choice experiment (NHCE)

The non-hypothetical CE experiment we informed the participants that each choice set was a real shopping scenario. In fact, the participants could receive any of options they had selected across all choice sets and they should pay for it the posted price. If participant did not like any product they can choose the "none of them" option. After finishing the main task, participants were given a choice set of 11options, and were asked to choose the product concept they prefer most.

After completing the two tasks and the survey, we asked for a volunteer to draw randomly a number between 1 and 2 to selecting the binding task. If the binding task was the main task, another volunteer was selected to randomly draw one of the 9 choice set[4] to determine which of the choice set will be the binding one. Hence, each participant receives his money and will buy the chosen option paying the corresponding price. In case, the participant chose the "none of them" option, (s)he received the money and did not buy any product. If the binding task is the holdout task, each participant had to buy the chosen option, paying the corresponding price. If the chosen option is the "none of them", the experiment finished for him (her).

Non-hypothetical rank conjoint analysis (NHRCA)

The same 10 choice sets were presented to each participant, who was asked to rank the options in each choice set from most to the least preferred option. In case the participant did not like any of presented alternatives, (s)he could choose the "none of them" option. The non hypothetical nature of the experiment was also revealed to participants since the beginning. After completing the main and the holdout tasks, a draw was made from a volunteer to select the binding task. If the main task was chosen as the binding task a volunteer draws the binding choice set. Following Lusk et al. (2008), to ensure us that the ranking treatment will be incentive compatible, the participant had to purchase the binding product with a probability proportional to the rank (s)he assigned. Then, each participant who did not choose the "none of them" option draws a number from 1 to 50 to select the biding product. If the number drawn was between 1 and 17, the participant should purchase the most preferred option and pay for it the posted price, if the number drawn was between 18 and 30 the second most preferred option will be the biding product; if between 31 and 40 the participant should be purchase the third option in (her)his preference ranking; if number drawn was between 41 and 47, the participant bought (her)his fourth preferred option; and between 48 and 50, the

[4] The last choice set (the number 10) was the same fifth choice set of the experimental design and was repeated at the end for assess the consistency and the internal validity. Therefore, for the equal probability to draw any choice set we will remove the tenth choice set.

participant should buy the least preferred option. If the binding task was the holdout task, the procedure was similar than in NHCE treatments.

Non-hypothetical best worst scaling (NHBWS)

Consistently with the previous treatments, the same 10 choice sets were presented to each participant in the main task. In this case, the participant was asked to choose firstly the most preferred option within the choice set, followed by the worst option of the four remaining options, followed by the second best option of the three remaining options, followed by the second worst option of the two remaining options. At the end of the day we obtains the preference ranking of each participant from the BWS treatment classifying the best option as the first option of the ranking, the second best option as the second option in the ranking, the third option of the ranking will be the remained option, the fourth option will be the second worst option, finally the last option of the ranking will be the first worst option. Once, the holdout task finished, the same procedure than in the NHRCA was followed to get the binding product.

Identification of attribute non-attendance

In the present study, attribute non-attendance information, at both serial (ST) and choice tasks (CT), is obtained by asking supplementary questions whether respondents have ignored some specific attributes or not. At choice task (CT), after completing each choice set, respondents were asked to report the attribute(s) they ignored when choosing among the different alternatives shown in the choice set. However, at serial task (ST), respondents were asked to report the attribute(s) they ignored during the whole choice task, after completing all the choice sets.

Methodological approach

Based on the random utility theory (McFadden, 1973) and the Lancaster's theory on consumer demand (Lancaster, 1966), the ith individual's utility function U_{ijs} towards an option j from a choice set s can be decomposed into a deterministic component V_{ijs} and a stochastic component ε_{ijs}.

$$U_{ijs} = V_{ijs} + \varepsilon_{ijs} \quad (1)$$

The deterministic component is commonly specified as linear in parameters and includes variables that represent the attributes of the product concept and the characteristics of respondents. In the empirical specification, the deterministic component is given by:

$$V_{ijs} = \beta_0 NoBuy + \beta_{EVOO} EVOO_{ijs} + \beta_{OO} OO_{ijs} + \beta_{Manf} Manf_{ijs} + \beta_{CAT} CAT_{ijs} + \beta_{RSp} RSp_{ijs} + \beta_{price} price_{ijs} \quad (2)$$

In Eq. (2) the attributes' levels (i.e. extra virgin olive oil (EVOO), olive oil (OO), Manufacturer label (Manf), Catalonian origin (CAT) and the "Rest of Spain" origin (RSp)) were effect coded (-1, 0, 1)[5], except for the price that was coded as a linear variable. The parameter "NoBuy" represents the no-choice option and has been coded as a dummy variable that takes the value 1 when the no-choice option is chosen by participant; and 0, otherwise.

In the case of the discrete choice data obtained in the NHCE treatment, the generalized multinomial logit model (GMNL) was used to estimate the partworths (i.e. β_0, $\beta_{EVOO,}$ $\beta_{OO,}$ β_{Manf}, β_{CAT}, β_{RSp} and β_{price}) . The generalized multinomial logit model allows us to accommodate both preference and scale heterogeneity (Fiebig et al. (2010).

Depending on the choice of distributions for the coefficients this can lead to WTP distributions which are heavily skewed (e.g. very large WTP values) and that may not even have defined moments (Train and Weeks, 2005; Scarpa et al., 2008). A common approach to dealing with this potential problem is to specify the price coefficient to be fixed. Nonetheless, it is often unreasonable to assume that all individuals have the same preferences for price (Meijer and Rouwendal, 2006). Train and Weeks (2005) suggest another way to get around this problem that consists in estimating the model in WTP space rather than in preference space. This involves estimating the distribution of willingness to pay directly by re-formulating the model in such a way that the coefficients represent the WTP measures. In the reformulated models, the a priori assumptions about the distributions of the parameters are made on the WTP rather than the attribute coefficients.

The specification in equation (2) parameterizes utility in "preference space". The model in WTP space consists in rewriting equation (2) as:

$$V = \beta_0 NoBuy + \beta_{price}\left[Price + \frac{\beta_{EVOO}}{\beta_{price}} EVOO + \frac{\beta_{OO}}{\beta_{price}} OO + \frac{\beta_{CAT}}{\beta_{price}} CAT + \beta Mant \beta price Manf + \beta RSp \beta price RSp + \varepsilon \right. \quad (3)$$

Equation (3) can be rewritten as:

$$V = \beta_0 NoBuy + \beta_{price}\left[Price + \theta_{EVOO} EVOO + \theta_{OO} OO + \theta_{CAT} CAT + \theta_{Manf} Manf + \theta RSp RSp + \varepsilon \right. \quad (4)$$

where $\theta_i = \beta_i / \beta_{price}$ represent individuals' willingness to pay estimates.

As shown in Train (2003), the unconditional probability that consumer *i* chooses the option *j* in the choice set *s* is as follows:

[5] The attribute levels virgin olive oil (VOO), private label (PRV), and Andalusia (AND) were considered as the baseline for the attributes: type of olive oil, brand, and origin, respectively.

$$Prob_i\{j\ is\ chosen\} = \int L_{ij}\left(\theta_{ij}\right) f(\theta_i/b) d\beta_i \quad (5)$$

where $f(\theta_i/b)$ is the density function of the coefficients θ_i. b refers to the moments (the mean and standard deviation) of the parameters' distributions and $L_{ij}\left(\beta_{ij}\right)$ is the conditional probability that individual i chooses the option j. $L_{ij}\left(\beta_{ij}\right)$ is given by:

$$L_{ij}\left(\beta_{ij}\right) = \frac{e^{V_{ij}}}{\sum e^{V_{ik}}} = \frac{e^{\beta_{ij}X_{ij}}}{\sum e^{\beta_{ik}X_{ik}}}, with\ k \epsilon C_s \quad (6)$$

In the case of the 'choice' data obtained in the NHRCA and NHBWS treatments, we estimated the parworths using the rank-order generalized multinomial logit (RO-GMNL) model (Lusk et al., 2008). The RO-GMNL assumes that the probability of a particular ranking of the product concepts presented in a choice set is the product of the multinomial choice probability for always choosing the best of the remaining options. That is, the probability (L_{ij}) that an individual *i* ranks the five product concepts A, B, C, D and E as follows A> B> C> D> E will be modeled as the product of the probability of choosing A as the best option from the choice set (A, B, C, D, E), the probability of choosing B as the best option among the remaining options (B, C, D, E), the probability of choosing C as the best option among the remaining options (C, D, E), and the probability of choosing D as the best option among the remaining options (D, E). Therefore, L_{ij} is given by:

$$L_{ij}(rankingA, B, C, D, E) = \frac{e^{V_{iA}}}{\sum_{j=A,B,C,D,E} e^{V_j}} * \frac{e^{V_{iB}}}{\sum_{j=B,C,D,E} e^{V_j}} * \frac{e^{V_{iC}}}{\sum_{j=C,D,E} e^{V_j}} * \frac{e^{V_{iD}}}{\sum_{j=D,E} e^{V_j}} \quad (7)$$

In the estimation of GMNL and RO-GMNL we assumed that all the partworths θ_{ij} of our empirical model are random and follow a normal distribution with mean θ and variance-covariance matrix Ω, as they are not independently distributed.

Modeling serial and choice task stated ANA information

To assess the effect of different cognitive effort spent by respondents in the different CA response formats in their attribute processing strategies, we estimate GMNL in the different following cases:

1. Without taking into account the ANA information, admitted that all the attributes were considered by the respondents when making their choices, named full attribute attendance (FAA).
2. Modeling ANA information at both serial (ST) and choice (CT) tasks by restricting the marginal utility coefficients of ignored attributes to zero.

Validating Serial and Choice task in Stated ANA information

Following Scarpa et al. (2013) and Caputo et al. (2017), we use a vector of k attendance indicators for each of the respondent *i*, one for each attribute *k*. we denote the generic

element of such vector as 1_{ik} (A=0) if respondent *i* stated having ignored the attribute k, and 1_{ik} (A=1) if the respondent *i* stated having attended it. The significance of the coefficient estimates for the ignored attributes can be used as a validation method. If the estimates for the attributes stated as being ignored are different from zero, then this would indicate that respondents did not fully ignore these attributes. We explore this in both the serial and choice task approaches.

The concordance between Stated and Inferred ANA

Following Caputo et al. (2017), the concordance between the two alternative ways to take with ANA such as Stated and Inferred methods, has been exploring by inferring the incidence of ANA in the sample using an Equality Constrained Latent Class model (ECLC) for panel data. The membership probabilities from the ECLC model estimates can then be used to explore the concordance of the ECLC model with the frequencies of the self-reported ANA information at both the serial and the choice task levels across the CA methods studied.

Willingness to pay

To test the statistical significance of possible differences of the estimated WTP space for each attribute across attribute processing approaches (i.e. FAA, ST, and CT) for each treatment, we follow the same method applied in Magistris et al. (2013). The method consists in pooling the data for each pair of attribute processing approaches applied in each treatment (i.e. FAA and ST, FAA and CT, and ST and CT). We then estimate an extended utility function as shown in equation 8. *dtrt* is a dummy variable take the number 1 for the first approach (for example FAA or ST) and 0 for the other second approach that we want to compare to the first one (for example CT or ST).

The extended utility function for the WTP space is given by:

$$V = \beta_0 NoBuy + \beta_{price}\left[Price + \theta_{EVOO}EVOO + \theta_{OO}OO + \theta_{CAT}CAT + \theta_{Manf}Manf + \theta_{RSp}RSp\right] + \gamma_{EVOO}(EVOO * dtrt) + \gamma_{oo}(OO * dtrt) + \gamma_{cat}(CAT * dtrt) + \gamma_{Manf}(Manf * dtrt) + \gamma_{RSp}(RSp * dtrt) + \varepsilon \quad (8)$$

As previously mentioned, the significance and the signs of the estimated γ will be the key point to detect differences in WTP spaces across treatments and facilitate us the sign of the inequality detected (Magistris et al., 2013).

External validity

To assess the external validity of the estimated parameters we have used the estimated partworths to predict the respondent's choice in the holdout task. Then, a hit rate[6] is calculated by comparing the predicted participants' decisions using the maximum utility, to their real decision done in the choice set of holdout task for each treatment. The Z-test for independent samples was used to assess the difference between hit rates across treatments taken into account the different attribute processing approaches.

Results and discussion

As mentioned before, at both serial and choice tasks approaches, respondents were asked to state whether they considered or ignored each of the attributes. As it reported in table 1, at serial task, the results show that 70% to 82% of participants reported to have ignored at least one attribute in the different CA formats. As may be seen, the lowest percent of respondents (18%) that reported to have attended all attributes was observed in NHCE treatment, however, the results were practically similar in the other treatments (NHRCA, and NHBWS). Although the four attributes and its levels were explained to the participants prior to each treatment, the low consciousness from the participants towards all attributes was observed in NHCE treatments in respect to NHRCA and NHBWS. This could be explained by, as the participants were randomly distributed across treatments, the samples participated in NHRCA and NHBWS were more interested about the attributes levels considered in the experiment and more awareness about the objectives of study. Furthermore, the results show that across treatments 0% of respondents have randomly chosen between the alternative. That is, the respondents when make their choices at least take into consideration one attribute. Additionally, we can observe that 3 % of respondents, taken into account only one attribute, in other words, they admitted lexicographic behavior when make their choices.

Table 1. Number of attributes ignored by respondents in serial task

	Treatments		
	NHCE	**NHRCA**	**NHBWS**
	% of Respondents	% of Respondents	% of Respondents
0	18.18	29.09091	30.90
1	56.36	43.63636	45.45
2	25.45	27.27273	20
3	0	0	3.63
4	0	0	0

[6] The hit rate in this case corresponds to the ratio of the total number of hits about the sample size in each treatment. The hit is defined as the success when the model correctly predicts the respondent's actual choice in the holdout task.

Table 2. Number of attributes ignored by respondents in choice task

	CT1	CT2	CT3	CT4	CT5	CT6	CT7	CT8	CT9
					NHCE				
0	14.54	12.72	21.81	12.72	14.54	12.72	20	14.54	16.36
1	54.54	65.45	50.90	56.36	56.36	54.54	52.72	52.72	49.09
2	29.09	20	21.81	29.09	27.27	27.27	27.27	30.90	34.54
3	1.81	1.81	5.45	1.81	1.81	5.45	0	1.81	0
4	0	0	0	0	0	0	0	0	0
					NHRCA				
0	18.18	25.45	20	23.63	21.81	23.63	23.63	21.81	27.27
1	40	47.27	40	41.81	43.63	40	41.81	43.63	40
2	41.81	21.81	38.18	34.54	30.90	32.72	32.72	25.45	30.90
3	0	5.45	0	0	1.81	3.63	0	5.45	1.81
4	0	0	1.81	0	1.81	0	1.81	3.63	0
					NHBWS				
0	10.90	14.54	16.36	18.18	18.18	16.36	21.81	14.54	21.81
1	50.90	40	40	40	40	36.36	38.18	49.09	38.18
2	32.72	38.18	38.18	38.18	36.36	41.81	34.54	32.72	36.36
3	5.45	5.45	5.45	3.63	5.45	5.45	5.45	3.63	3.63
4	0	1.81	0	0	0	0	0	0	0

At choice task level, the table 2 recorded information about ANA for each of the nine choice tasks. Similar results, as at serial task, could be observed. In average, only 15% to 30% of the respondents self reported to have considered, throughout their decision process, all the four attributes and that le lowest percentage of respondents (15%) was observed in NHCE treatment. Additionally, the results show that the respondents did not follow the same attributes processing strategy in all of nine choice tasks. Therefore, consistent with Scarpa et al. (2010) and Caputo et al. (2014), collecting information of ANA at choice task level could be more informative than on serial task.

Furthermore, table 3 reported the most ignored attributes, at both serial and choice tasks, in the different treatments. The results revealed that the most ignored attributes were the brand and the origin of the product, contrary to type of olive oil and the price which were the most attended. These results were consistent in both serial and choice tasks. Also, the differences in ignorance' level of attributes could be observed across treatments. However, the question remains open was, what effect have the different attribute processing strategies in model performance, external validity, and participants' WTP, across treatments.

Table 3. Attributes ignored by respondents in serial and choice tasks

	Treatments					
	NHCE		**NHRCA**		**NHBWS**	
	ST	**CT**	**ST**	**CT**	**ST**	**CT**
	% of Respondents	% of Time	% of Respondents	% of Time	% of Respondents	% of Time
Type of olive oil	1.81	4.44	7.27	9.09	10.90	18.78
Brand	67.27	63.43	52.72	54.94	45.45	56.36
Origin	21.81	28.48	21.81	28.88	36.36	46.26
Price	16.36	20	16.36	23.43	3.63	8.48

ST: serial task; CT: choice task.

We now turn our attention to illustrate the results of the estimates and to discussing their implications. The estimates of GMNL models were reported in the table 4 and table 5. In table 4 we report the means and the standard deviations of the estimated WTP space in the different treatments considering only the best option. That is, we report the estimates corresponding to the three treatments where the dependent variable has been coded in a similar way. Particularly, in NHCE the dependent variable takes the value of 1 when the option is chosen and 0 otherwise; while in NHRRCA and NHRBWS the dependent variable is coded as 1 when the option is ranked first and 0 otherwise. In the table 5, we present the results of the estimation of the ranking models (i.e., NHRCA and NHBWS) taking into account the full ranking information. Furthermore, the characteristics of model performance of the different estimated models were reported in the table 6 and table 7, when only the best option was coded and when the full ranking information taken into account respectively.

Table 4. ANA models across serial and choice task and full attendance models in the different treatments
Considering only the best option

	Treatments								
	NHCE			NHRRCA			NHRBWS		
	FAA	ST	CT	FAA	ST	CT	FAA	ST	CT
	Estimated parameters								
NoBuy	-3.129***	-2.597***	-1.714***	-4.152***	-3.809***	-3.446***	-4.867***	-4.894***	-3.524***
(SE)	(0.32)	(0.292)	(0.225)	(0.471)	(0.348)	(0.326)	(0.373)	(0.385)	(0.331)
Extra virgin	0.889***	1.188***	1.176***	1.636***	1.391***	1.49***	1.35***	1.413***	1.417***
Olive oil	(0.239)	(0.172)	(0.262)	(0.269)	(0.246)	(0.243)	(0.343)	(0.136)	(0.189)
(EVOO)									
Olive oil	-0.891***	-0.768***	-0.855***	-1.698***	-1.561***	-1.608***	-1.287***	-1.254***	-1.332***
(OO)	(0.326)	(0.173)	(0.263)	(0.34)	(0.298)	(0.315)	(0.329)	(0.167)	(0.229)
Manufacturer	0.120	0.419***	0.612***	0.281	0.486***	0.415**	0.244	0.458***	0.243*
label (Manf)	(0.159)	(0.151)	(0.187)	(0.212)	(0.126)	(0.181)	(0.16)	(0.117)	(0.128)
Catalonia	0.626**	0.650***	1.044***	0.472**	0.237	0.551***	0.861***	1.519***	1.084***
(CAT)	(0.251)	(0.169)	(0.272)	(0.229)	(0.193)	(0.202)	(0.209)	(0.145)	(0.156)
Rest of Spain	-0.447*	-0.546***	-0.779***	-0.91***	-0.784***	-1.117***	-0.695***	-0.889***	-0.919***
(RSp)	(0.24)	(0.138)	(0.228)	(0.248)	(0.188)	(0.235)	(0.171)	(0.157)	(0.173)
Price	1	1	1	1	1	1	1	1	1
	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)
	Standard deviation of estimated random parameters								
EVOO	1.941***	1.408***	2.00***	1.646***	1.775***	1.581***	2.658***	2.253***	3.116***
	(0.278)	(0.225)	(0.235)	(0.229)	(0.248)	(0.226)	(0.491)	(0.152)	(0.202)
OO	1.889***	1.349***	1.982***	1.499***	1.631***	1.72***	3.115***	2.532***	3.856***
	(0.30)	(0.172)	(0.212)	(0.261)	(0.27)	(0.293)	(0.556)	(0.211)	(0.306)
Manf	0.385**	0.994***	0.943***	0.601**	0.726***	0.772***	0.433*	1.12***	0.552***
	(0.175)	(0.074)	(0.081)	(0.267)	(0.083)	(0.09)	(0.236)	(0.069)	(0.062)
CAT	1.082***	1.65***	1.606***	0.872**	1.172***	1.272***	0.967***	1.129***	1.073***
	(0.231)	(0.209)	(0.171)	(0.35)	(0.221)	(0.198)	(0.274)	(0.153)	(0.094)
RSp	0.905***	1.244***	0.974***	0.763*	0.724***	0.992***	0.545	0.763***	0.379***
	(0.226)	(0.174)	(0.187)	(0.411)	(0.17)	(0.177)	(0.335)	(0.116)	(0.145)
Price	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)

FAA: full attribute attendance; ST: serial task; CT: choice task;

Table 5. ANA models across serial and choice task and full attendance models in the different treatments
Considering the full ranking information

	Treatments					
	NHRCA			NHBWS		
	FAA	ST	CT	FAA	ST	CT
	Estimated parameters					
NoBuy	-4.496***	-4.948***	-4.797***	-4.071***	-4.036***	-3.682***
(SE)	(0.14)	(0.179)	(0.197)	(0.156)	(0.145)	(0.281)
Extra virgin Olive	0.694***	0.865***	0.679***	1.387***	1.699***	1.747***
oil (EVOO)	(0.083)	(0.085)	(0.075)	(0.108)	(0.101)	(0.109)
Olive oil	-0.653***	-1.047***	-0.85***	-1.498***	-1.696***	-1.89***
(OO)	(0.079)	(0.05)	(0.075)	(0.105)	(0.141)	(0.127)
Manufacturer	0.675***	1.05	0.957***	0.207**	0.248*	0.544***
label (Manf)	(0.202)	(0.903)	(0.347)	(0 .103)	(0.133)	(0.093)
Catalonia	1.275***	-0.119	1.101***	0.859***	0.491***	0.955***
(CAT)	(0.115)	(0.154)	(0.219)	(0.093)	(0.179)	(0.144)
Rest of Spain	-1.510***	-0.54***	-0.90***	-0.859***	-0.543***	-1.00***
(RSp)	(0.162)	(0.157)	(0.204)	(0.085)	(0.201)	(0.119)
Price	1	1	1	1	1	1
	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)
	Standard deviation of estimated random parameters					
EVOO	2.363***	2.51***	2.398***	1.420***	1.717***	1.771***
	(0.211)	(0.18)	(0.223)	(0.098)	(0.121)	(0.114)
OO	1.958***	2.046***	2.008***	1.598***	2.29***	2.414***
	(0.15)	(0.119)	(0.201)	(0.093)	(0.101)	(0.134)
Manf	0.982***	1.666***	1.907***	0.344***	0.546***	0.715***
	(0.106)	(0.254)	(0.481)	(0.10)	(0.151)	(0.082)
CAT	1.088***	1.948***	0.95**	0.685***	1.801***	2.197***
	(0.13)	(0.388)	(0.424)	(0.109)	(0.259)	(0.163)
RSp	1.614***	1.40***	1.17***	0.591***	1.396***	1.993***
	(0.111)	(0.238)	(0.23)	(0.093)	(0.23)	(0.10)
Price	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)

FAA: full attribute attendance; ST: serial task; CT: choice task;

Table 5. Models' goodness of fits across serial and choice task and full attendance models
(Considering only the best option)

	Treatments								
	NHCE			NHRRCA			NHRBWS		
	Full AA	**ST**	**CT**	**Full AA**	**ST**	**CT**	**Full AA**	**ST**	**CT**
Nb of obs	2970	2970	2970	2970	2970	2970	2970	2970	2970
LL	-594.0309	-614.6017	-629.9250	-667.7204	-669.2338	-668.4700	-597.0711	-592.1884	-628.0239
AIC	2.497	2.580	2.642	2.795	2.801	2.798	2.509	2.490	2.634
BIC	2.701	2.784	2.846	2.999	3.005	3.002	2.713	2.694	2.838

FAA: full attribute attendance; ST: serial task; CT: choice task;

Table 6. Models' goodness of fits across serial and choice task and full attendance models
(Considering the full ranking information)

	Treatments					
	NHRCA			NHBWS		
	Full AA	**ST**	**CT**	**Full AA**	**ST**	**CT**
Nb of obs	7155	7155	7155	7107	7107	7107
LL	-1808.1663	-1798.5664	-1788.9827	-1783.4264	-1759.1345	-1791.6823
AIC	1.939	1.929	1.919	1.928	1.903	1.938
BIC	2.009	1.999	1.989	1.999	1.974	2.009

FAA: full attribute attendance; ST: serial task; CT: choice task;

Table 4 and table 5 report the means and standard deviations of WTP space estimates of GMNL modeling the information of ANA from both ST and CT and contrast them with the estimates of the FAA model, in the different treatments. Table 4 and table 5 show that the results are generally consistent across the different estimated models. In general, the results show that almost of the estimated partworths of models across both ST and CT as well as from FAA model are significant at 1% level and have the same and the expected signs. In particular, the results indicate surveyed consumers in all the treatments are more likely to choose extra virgin olive oil than non-virgin olive oil. The consumers were also found to prefer manufacturer label over private label and local (i.e. Catalonia) olive oil over non-local olive oil (i.e. olive oil from Andalusia and the rest of Spain).The negative estimate of the price shows that the higher the price was, the lower the utility associated with a product. Also, the negative estimate of the "No Buy" variable implies that participants, in the different choice treatments, tend to highly prefer one of the real olive oil as opposed to "not purchase" alternative.

Additionally, almost of the standard deviations of the random estimates from all treatments are statistically significant at 1% level implying the presence of preference heterogeneity across individuals. The evidence of preference heterogeneity persists in both cases, serial and choice tasks. Consistent with Hess et al. (2013) findings, attribute non-attendance seem to not capture almost of the preference heterogeneity, in fact, could be true share with a small part of the preference heterogeneity, but there is substantial remaining heterogeneity in the data associated with true respondents' taste heterogeneity. Also, the highest significance of standard deviation of random estimates could be due that when respondents self reported to ignore some attributes, effectively, they not make what they said. On other words, the respondents how stated to ignore some attribute, not really fully ignore that attributes but assigned less importance.

Furthermore, the results reported in table 6 reveal that, considering only the most preferred option, when modeling ANA information not significantly improved the goodness-of-fit of the estimated models in ST as well as in CT, in respect to FAA models in NHCE and NHRRCA treatments. For NHRBWS treatment, the results show that modeling ANA information improved the model performance except in the case of ST in respect to FAA. However, take into account the full ranking information, the results reveal that modeling ANA information the model better fit the data in both cases in ST and CT. Also, the results show that the higher goodness-of-fit is noted when modeling ANA information in CT comparing with ST. In respect to NHBWS treatment, the results are consistent with the first

case. That is, either taken into consideration the full ranking information or just coded the best option, the results reveal that, just when modeling ANA information from ST, the model better fit the data compared with FAA model.

Now, we assess the effect of ANA statements from both ST and CT in WTP space estimates. The results of equality test of consumers' WTP space through attribute processing approaches is displayed in table 7.

Table 7. Hypothesis test of equality WTP space values across attribute processing approaches

	Full attendance attribute (FAA) vs Serial task (ST)				
	$\gamma_{EVOO*dtrt.FAA}$	$\gamma_{OO*dtrt.FAA}$	$\gamma_{Manf*dtrt.FAA}$	$\gamma_{CAT*dtrt.FAA}$	$\gamma_{Rsp*dtrt.FAA}$
NHCE	-0.179	0.057	-0.118	-0.161	0.198
	(0.247)	(0.265)	(0.191)	(0.272)	(0.172)
RRCA	0.049	-0.129	0.129	0.105	-0.315**
	(0.156)	(0.181)	(0.143)	(0.136)	(0.137)
RBWS	0.502***	-0.809***	0.009	-0.187	-0.297**
	(0.164)	(0.214)	(0.117)	(0.125)	(0.124)
RCA	0.073	-0.124**	0.094***	0.244***	-0.411***
	(0.072)	(0.06)	(0.028)	(0.038)	(0.048)
BWS	0.907***	-0.976***	0.024	0.41***	-0.507***
	(0.063)	(0.064)	(0.06)	(0.082)	(0.066)
	Full attendance attribute (FAA) vs Choice task (CT)				
	$\gamma_{EVOO*dtrt.FAA}$	$\gamma_{OO*dtrt.FAA}$	$\gamma_{Manf*dtrt.FAA}$	$\gamma_{CAT*dtrt.FAA}$	$\gamma_{Rsp*dtrt.FAA}$
NHCE	-0.147	0.08	-0.139	0.018	0.13
	(0.252)	(0.264)	(0.146)	(0.251)	(0.21)
RRCA	0.518***	-0.459***	0.075	0.276**	-0.501***
	(0.154)	(0.161)	(0.093)	(0.138)	(0.131)
RBWS	0.242	-0.509**	0.041	-0.313**	-0.157
	(0.17)	(0.208)	(0.113)	(0.146)	(0.157)
RCA	0.148***	-0.148***	0.156***	0.192***	-0.261***
	(0.057)	(0.053)	(0.036)	(0.046)	(0.056)
BWS	0.350***	-0.384***	0.062	0.389***	-0.459***
	(0.081)	(0.075)	(0.064)	(0.058)	(0.051)
	Serial task (ST) vs Choice task (CT)				
	$\gamma_{EVOO*dtrt.ST}$	$\gamma_{OO*dtrt.ST}$	$\gamma_{Manf*dtrt.ST}$	$\gamma_{CAT*dtrt.ST}$	$\gamma_{Rsp*dtrt.ST}$
NHCE	0.299	-0.334	0.048	-0.067	0.084
	(0.261)	(0.268)	(0.194)	(0.222)	(0.208)
RRCA	0.407**	-0.29	0.117	0.125	-0.386**
	(0.183)	(0.20)	(0.129)	(0.144)	(0.166)
RBWS	1.036**	-1.05**	0.108	0.218	-0.275
	(0.404)	(0.426)	(0.129)	(0.239)	(0.178)
RCA	0.085**	-0.077	0.089	0.194***	-0.42***
	(0.04)	(0.056)	(0.09)	(0.045)	(0.055)
BWS	0.578***	-0.583***	0.068	0.334***	-0.468***
	(0.059)	(0.07)	(0.083)	(0.062)	(0.069)

When assessing the difference in consumers' WTP deducing from attribute processing approaches (FAA, ST and CT), the results reveal that, in NHCE treatment, there are no significant differences between WTPs in all cases. In NHRRCA treatment, modeling ANA information deduced from ST don't seem have effect in consumers' WTP compared to FAA. However, the results reveal that there are significant differences between consumers' WTP taken into account attribute non attendance information from CT approach and consumers' WTP taken into FAA information. Also, in the case of NHRBWS, modeling ANA information has significant effect in consumers' WTP, independently to attribute processing approaches (ST or CT). Furthermore, taken into consideration the full ranking information (NHRCA and NHBWS), the results show that, regardless to attribute processing approaches, modeling ANA information seem to have clear effect in consumers' WTP.

However, Consistent with Scarpa et al. (2012) findings, in term of marginal WTP estimates, the results reveal that across the treatments neither of the two ANA approaches appears to be a clear winner. In fact, as the ANA statements approaches (ST and CT) are considered as reference levels in our tests, the sign positive of estimated coefficient associated to dummy treatments variables (γ) will demonstrate that the first treatment (when modeling the full attribute attendance information, FAA) overestimate consumers' WTP. Nonetheless, the results show that the estimated coefficients (γ) have positive signs, in some cases, and in others have negative signs. That is, taken into consideration ANA information deduced from ST as well as from CT have in some cases underestimation effect in consumers' WTP and in others have overestimation effect in respect to FAA approach. In accordance with Scarpa et al. (2010) and Caputo et al. (2014) the direction of the changes in respondents' WTPs when accounting for ANA remains an empirical issue.

Finally, as mentioned above, we assess the implications of taking into account the ANA information on the external predictive powers of the estimated parameters across treatments. Table 8 reports the hit rate of participants in external validity analysis across the different treatments and across ANA approaches. However, the results of equality test of hit rates are displayed in table 9. The results reveal that regardless to considerate the full ranking information or modeling just only the most preferred option, BWS treatment present the higher predictive power of their estimated parameters. However, there is no significant difference in respect to NHCE and other treatments. Furthermore, the results show that modeling ANA information don't seem to improve significantly the predictive power of estimated parameters in all treatments, independently to ANA approaches ST or CT.

Table 8. External validity across serial and choice tasks and full attendance attribute

Treatments	External validity		
	Full AA	**ST**	**CT**
	Hit rate (%)	**Hit rate (%)**	**Hit rate (%)**
NHCE	27.272	27.272	29.090
NHRRCA	23.636	18.181	18.181
NHRBWS	34.545	30.909	32.727
NHRCA	18.181	9.090	21.818
NHBWS	30.909	32.727	36.363

Table 9. Equality test of external validity tests across treatments

		Nº of choices	Nº correct of predictions	Hit rate (%)	*p-value*
NHCE					
FAA vs ST	FAA	55	15	27.272	1
	ST	55	15	27.272	
FAA vs CT	FAA	55	15	27.272	0.832
	CT	55	16	29.090	
ST vs CT	ST	55	15	27.272	0.832
	CT	55	16	29.090	
RRCA					
FAA vs ST	FAA	55	13	23.636	0.481
	ST	55	10	18.181	
FAA vs CT	FAA	55	13	23.636	0.481
	CT	55	10	18.181	
ST vs CT	ST	55	10	18.181	1
	CT	55	10	18.181	
RBWS					
FAA vs ST	FAA	55	19	34.545	0.684
	ST	55	17	30.909	
FAA vs CT	FAA	55	19	34.545	0.840
	CT	55	18	32.727	
ST vs CT	ST	55	17	30.909	0.837
	CT	55	18	32.727	
NHRCA					
FAA vs ST	FAA	55	10	18.181	0.164
	ST	55	5	9.090	
FAA vs CT	FAA	55	10	18.181	0.633
	CT	55	12	21.818	
ST vs CT	ST	55	5	9.090	0.064
	CT	55	12	21.818	
NHBWS					
FAA vs ST	FAA	55	17	30.909	0.837
	ST	55	18	32.727	
FAA vs CT	FAA	55	17	30.909	0.544
	CT	55	20	36.363	
ST vs CT	ST	55	18	32.727	0.688
	CT	55	20	36.363	

Conclusion

Attribute non-attendance (ANA) is an important issue for researchers engaged in conjoint analysis. Researchers have reported that respondents might adopt specific attribute processing strategy, while evaluating the different presented alternatives in the experiment, by ignoring some of the attributes studied violating thus the continuity axiom of consumer behavior theory. ANA information can be assessed by two methods, or asked the respondents directly what of the attributes were ignored during a survey, or indirectly inferred its. In both cases, past studies shown that if ANA information was not be modeling could be caused a bias in parameter estimates and leading to over or under-estimation of respondents' WTPs.

Accordingly, the present study aimed to investigate (1) the effect of respondents' cognitive effort spent in different CA response formats in respondents' self reported statements related to ANA; (2) to evaluate which between the serial and choice tasks ANA approaches is more suitable to capture ANA consumer processing strategy across the different CA response formats; (3) to assess the implications of taking into account the collected information on ANA on respondents' willingness to pay and on external predictive powers of the estimated parameters. To answer our questions, three treatments were carried out non hypothetical choice experiment (NHCE), non hypothetical ranking conjoint analysis (NHRCA), and non hypothetical best worst scaling (NHBWS). the data were analyzed using Generalized multinomial logit model (GMNL) taking into account the unobserved effect of the correlation that could be exist between the attributes.

The results show that 70% to 82% of participants reported to have ignored at least one attribute across the different CA format. The results revealed that the most ignored attributes were the brand and the origin of the product, contrary to type of olive oil and the price which were the most attended. Furthermore, the results reveal that taking into account ANA information significantly improved the goodness-of-fit of the estimated models in respect to Full AA models, especially for treatments that taken into consideration the full ranking information as NHRCA and NHBWS. Additionally, in NHRCA treatment, we can observe that when modeling ANA information deduced from choice task the model better fit the data than in serial task. However, take into consideration ANA information doesn't improve significantly the goodness-of-fit of the estimates models, regardless to processing approaches, when only the most preferred option is modeled as NHCE and NHRRCA.

In term of marginal WTP estimates, in almost of cases except in NHCE treatment, accounting for attributes non attendance information seems to have significant effect in consumers' WTP compared with full attribute attendance information. However, when

comparing the results between the two ANA approaches, the results reveal, that across the treatments, neither of the two ANA approaches appears to be a clear winner. In some cases marginal WTPs estimates are overestimated and in others are underestimated, in respect to FAA. Finally, in terms of estimated parameters predictive power, modeling ANA information not seem to improve significantly external predictive power of associated estimates parameters, in respect to Full AA model.

It is noteworthy that these results discussed in this paper need to be compared with results deduced from the inferred ANA approaches, and therefore our results can be generalized. However, for lack of time, the second part of the results will be included in the final version of the paper if gets accepted in the conference.

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