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# Comparing results of ranking conjoint analyses, best–worst scaling and discrete choice experiments in a nonhypothetical context\*

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This study assesses the comparability of discrete choice experiment (DCE), ranking conjoint analysis (RCA) and multiprofile best–worst scaling (BWS) in a nonhypothetical context in terms of estimated partworths, willingness to pay (WTP), response consistency and external validity. Overall, the results suggest that: (i) the conjoint analysis formats that were used in this study provide similar estimated WTP, but different estimated partworths and computed external validity; (ii) the inclusion of the full ranking information in the estimation of the parameters of interest affects the estimated partworths, but not the estimated WTP; and (iii) it is more appropriate to use multiprofile BWS over DCE and RCA because it has better predictive power of consumers' preferences and provides estimated WTP comparable to those obtained in the others conjoint analysis formats. The BWS' cognitive process could be considered clearness for participants implying significant increment of its predictive power.

**Key words:** best–worst scaling, discrete choice experiment, external validity, ranking conjoint analysis, willingness to pay.

## 1. Introduction

Since its introduction, conjoint analysis (CA) has become one of the most popular research tools to elicit consumer preference and willingness to pay (WTP). CA is a stated-preference method that requires human participants to rate, rank or choose between competing products or alternatives (Louviere and Street 2000). Currently, discrete choice experiment (DCE) is the most widely used CA format. In CE, respondents are shown a set of combinations of attributes, that is profiles, and are asked to indicate which of the

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profiles they would purchase. DCE gained popularity because it can mimic real-market settings where consumers are offered competing products and asked to purchase the product that aligns with their preferences. However, DCE only allows to collect data on the most-preferred option but does not provide information on consumer's preferences towards the remaining option (the options in a choice set excluding the chosen option) in a choice set (Louviere *et al.* 2008; Lusk *et al.* 2008; Lancsar *et al.* 2013). In contrast to DCE, participants in a ranking conjoint analysis (RCA) are provided with a set of product concepts and are asked to rank them from the most to the least-preferred product concept. The use of RCA as an alternative to DCE is gaining popularity since it provides information not only on the most-preferred product concept, but also on consumer preferences for all the product concepts included in a choice set, which in turn provides more efficient preference estimates (Louviere *et al.* 2008; Lusk *et al.* 2008; Chang *et al.* 2009).

Despite the extensive use of DCE and RCA over the last two decades, few studies have been published on their performance in terms of estimated partworths, the predictive power of estimated partworths and the reliability of the WTP values deduced from the estimated partworths (Boyle *et al.* 2001; Holmes and Boyle 2001; Morrison and Boyle 2001; Siikamäki and Layton 2007; Caparrós *et al.* 2008; Pignone *et al.* 2011; Akaichi *et al.* 2013). To illustrate, Boyle *et al.* (2001) compared DCE, RCA and recoded RCA (RRCA), which means the participant's response is coded as '1' when the product concept presented in the choice set is ranked first and '0' otherwise. Boyle *et al.* (2001) found differences between the results obtained in DCE and RCA. They argued that these differences could be explained by the various cognitive processes used by subjects in each CA format. Similarly, Caparrós *et al.* (2008) pointed out that DCE and RRCA provide comparable results when a similar experimental design is used for both DCE and RCA. Notably, Akaichi *et al.* (2013) confirmed the results found by Caparrós *et al.* (2008) for small choice sets, that is four alternatives; however, they found discrepancies between respondents' preferences in DCE and RRCA when large choice sets; that is, eight alternatives, were used. Finally, Chang *et al.* (2009) showed that the nonhypothetical RCA outperforms both the hypothetical and nonhypothetical DCE when the full ranking information is considered in the estimation.

Finn and Louviere (1992) introduced another CA format named, best-worst scaling (BWS). There are three cases of BWS, which differ in terms of the complexity of the items or options assessing: BWS object case; BWS profile case; and BWS multiprofile case (Flynn and Marley 2014). The last case of BWS approach (MBWS), which considered in this study, consists of asking respondents to first choose the best and the worst option, then the second-best and the second-worst options from the remaining options and so on until a complete preference ordering of all the product concepts included in a choice set is obtained (Scarpa

*et al.* 2011). Compared with RCA, MBWS has the advantage of being aligned with the random utility theory (Louviere and Flynn 2010). Furthermore, the choice task in MBWS is easier for respondents to understand thanks to their human skills at identifying extremes (Marley and Louviere 2005; Vermeulen *et al.* 2010; Potoglou *et al.* 2011; Flynn and Marley 2014). Similar to RCA, the additional choice information obtained from MBWS has been shown to improve the statistical efficiency of choice models (Lancsar *et al.* 2013). Nevertheless, none of the aforementioned studies that compared different CA formats assessed the comparability of MBWS to both DCE and RCA.

To the best of our knowledge, only two published studies have compared BWS to DCE or to RCA. Potoglou *et al.* (2011) compared welfare estimates obtained in DCE and BWS experiments. They found that the differences in the estimated preference weights between the two CA formats were not statistically significant. Lagerkvist (2013) compared the results obtained in RCA and BWS and found that the rank, choice probability and attribute dominance obtained in RCA and BWS were significantly different. While their findings informed our research, our study is different from those of Potoglou *et al.* (2011) and Lagerkvist (2013) in five key ways. First, we assessed the comparability of results obtained in the three CA formats, that is DCE, RCA and MBWS. Particularly, we assessed the comparability of the three CA formats in terms of estimated partworths, predictive power, response consistency and WTP.

Second, Potoglou *et al.* (2011) and Lagerkvist (2013) conducted different CA formats in hypothetical settings. Nonetheless, the divergence in valuations between hypothetical and nonhypothetical preference and value-elicitation methods, for example DCE, contingent valuation and experimental auction, is well documented in the literature (List and Gallet 2001; Little and Berrens 2004; Murphy *et al.* 2005; Chang *et al.* 2009; Moser *et al.* 2014). Notably, these studies found that participants in hypothetical elicitation methods overestimated their preferences and WTP. This behaviour is commonly explained by the fact that in the absence of any moral or monetary cost that prevents subjects deviating from their actual behaviour, participants in hypothetical elicitation methods will not put enough cognitive effort into the elicitation tasks and may not reveal their true preferences and values (Lusk and Shogren 2007). Despite the well-documented negative effect of hypothetical bias, the majority of the studies that assessed the comparability of CA formats reported results from economic experiments conducted in hypothetical settings, with the exception of Chang *et al.* (2009) and Akaichi *et al.* (2013). Accordingly, due to the scepticism surrounding the validity of values obtained from

hypothetical CA formats, we conducted the DCE, the RCA and the MBWS in nonhypothetical settings.<sup>1</sup>

Third, Potoglou *et al.* (2011) and Lagerkvist (2013) used different experimental designs for the DCE, the RCA and the BWS. Therefore, the divergence of the estimates obtained by Lagerkvist (2013) in RCA and BWS could be a result of the variation in the experimental design used. To rule out the effect of this bias, we used an identical experimental design for DCE, RCA and MBWS. In the DCE, respondents were asked to indicate the product they prefer most. Comparatively, in RCA, respondents were asked to rank the product concepts from the most preferred to the least preferred, while in MBWS they were asked to indicate the best and the worst product concepts.

Fourth, with the exception of Akaichi *et al.* (2013), the previous studies that compared different CA formats did not test the external validity of their estimates. Testing the external validity of the estimates in CA is important since it allows for the assessment of the predictive power of the estimated choice models, which in turn constitutes one of the main reasons for using CA formats. To compare the external validity of the three CA formats, we used a nonhypothetical holdout choice task. Following Ding (2007) and Akaichi *et al.* (2013), the holdout task, that is a regular choice task, was held out of the partworths' estimation process since it is only used to assess the out-of-sample predictive power of the estimated partworths in the three CA formats.

Fifth, one of the main assumptions underlying the theory of stated preferences is that respondent preferences are stable and coherent (Brown *et al.* 2008). Nonetheless, according to Hoeffler and Ariely (1999), preference consistency or stability is positively correlated with choice experience and cognitive choice effort. For instance, in repeated choices, respondents are expected to be more precise and hence more consistent in their decisions due to the learning effect (Brouwer *et al.* 2010). On the other hand, when respondents face complex choice tasks, for example too many choice sets or too many product concepts per choice set, they are expected to be less precise and hence less consistent in their choices, when compared with respondents who face an easy choice scenario (Brouwer *et al.* 2010). In this study, we also compared the consistency of respondents' answers in DCE, RCA and MBWS to find out which of the three CA formats provide the highest level of response consistency. To test the consistency of respondents' answers, one of the choice sets given to respondents was repeated at the end of the main choice task.

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<sup>1</sup> If the respondents do not consider the endowment received from the experimenter as part of their own budget, the concern is participants may spend from this money differently than they would from their original income and reserve a different mental account for nonwindfall and windfall money (Arkes *et al.* 1994; Cummings and Taylor 1999).

## 2. Methodology

### 2.1 Design and the implementation of the experiment

In this study, three treatments were conducted in Barcelona, Spain: a nonhypothetical DCE (NHCE); a nonhypothetical RCA (NHRCA); and a nonhypothetical MBWS (NHMBWS). To assess the comparability of the three CA formats, 165 consumers were recruited. The sample of participants was randomly selected from different locations across Barcelona and its metropolitan area, using a stratified sampling procedure by age and gender. Participants were randomly and equally assigned to the three treatments.<sup>2</sup>

Olive oil was the food product used in the experiments, and the attributes and attribute levels were identified based on the literature review and the information collected from two focus groups of high-experienced to low-experienced consumers of olive oil. Accordingly, four attributes were considered; three of which have three levels including: (i) type of olive oil, that is extra virgin, virgin and olive oil; (ii) origin of olive oil, that is Andalucía, Catalonia (local olive oil) and the rest of Spain; and (iii) price, that is 2.20, 3.50 and 4.80 €/L, which accounts for 85 per cent of the price distribution of olive oil in the retail outlets operating in the city of Barcelona. Brand is the fourth attribute and has two levels: manufacturer label; and private label.

Given these attribute levels, a full factorial design of 54 ( $3^3 \times 2$ ) product concepts, that is 1-L bottles of olive oil, was generated. Notably, presenting respondents with 54 product concepts could, however, place a high level of cognitive burden on respondents. Therefore, Street and Burgess (2007) approach was followed to reduce the number of product concepts that participants have to evaluate. To explain, first, an orthogonal fractional factorial design of nine product concepts was generated. These nine product concepts were considered as the first option in each choice set. Since participants were provided with choice sets of five product concepts each, the second, the third, the fourth and the fifth option were generated using the generators (1000), (1111), (2121) and (2122), respectively. The way generators are used to obtain the remaining option, is clearly described in Street and Burgess (2007). The same experimental design (e.g. same number of choice sets, same options in each choice set) was used in the three treatments. The only difference is the task that respondents were required to perform (choosing in NHCE, ranking in NHRCA and identifying the best and worst option in NHBWS). The experiment design that was used in the three treatments consists in nine choice sets of five product concepts each plus the no-choice option. Examples of the choice sets used in each treatment are displayed in Figures 1–3.

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<sup>2</sup> The results of chi-square test showed that the null hypothesis of equality between the sociodemographic characteristics across treatments samples cannot be rejected at the 5 per cent significance level for gender, age, education and income.



Choice card ...			Identification Number: .....			
	Olive oil 1	Olive oil 2	Olive oil 3	Olive oil 4	Olive oil 5	Option 'No Buy'
Type of olive oil	Virgin	Virgin	Olive oil	Extra virgin	Virgin	None of the five olive oils
Brand	Manufacturer label	Manufacturer label	Private label	Manufacturer label	Private label	
Origin	Catalonia	Andalusia	Catalonia	Catalonia	Rest of Spain	
Price (€)	2.20	4.80	2.20	3.50	2.20	
	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Please mark the olive oil you would purchase or mark the option 'No buy' if you are not willing to purchase any of the five olive oils.						

Figure 1 An example of a choice set provided to participants in nonhypothetical discrete choice experiment.

Choice card ...			Identification Number: .....			
	Olive oil 1	Olive oil 2	Olive oil 3	Olive oil 4	Olive oil 5	Option 'No buy'
Type of olive oil	Virgin	Virgin	Olive oil	Extra virgin	Virgin	None of the five olive oils
Brand	Manufacturer label	Manufacturer label	Private label	Manufacturer label	Private label	
Origin	Catalonia	Andalusia	Catalonia	Catalonia	Rest of Spain	
Price (€)	2.20	4.80	2.20	3.50	2.20	
	<div><div>12</div><div>34</div><div>5</div></div>	<div><div>12</div><div>34</div><div>5</div></div>	<div><div>12</div><div>34</div><div>5</div></div>	<div><div>12</div><div>34</div><div>5</div></div>	<div><div>12</div><div>34</div><div>5</div></div>	<input type="checkbox"/>
Please rank the five olive oils from the most to the least preferred olive oil or mark the option 'No buy' if you don't like any of the five olive oils .						

Figure 2 An example of a choice set presented in nonhypothetical ranking conjoint analysis treatment.

At the beginning of the experiment, participants were informed that they would receive a participation fee of 15 Euros in cash at the end of their participation. Aware of the possible effect of windfall bias, we made

Choice card ...			Identification Number: .....			
	Olive oil 1	Olive oil 2	Olive oil 3	Olive oil 4	Olive oil 5	Option 'No buy'
Type of olive oil	Virgin	Virgin	Olive oil	Extra virgin	Virgin	None of the five olive oils
Brand	Manufacturer label	Manufacturer label	Private label	Manufacturer label	Private label	
Origin	Catalonia	Andalusia	Catalonia	Catalonia	Rest of Spain	
Price (€)	2.20	4.80	2.20	3.50	2.20	
	<input type="checkbox"/> B <input type="checkbox"/> 2B <input type="checkbox"/> W <input type="checkbox"/> 2W	<input type="checkbox"/> B <input type="checkbox"/> 2B <input type="checkbox"/> W <input type="checkbox"/> 2W	<input type="checkbox"/> B <input type="checkbox"/> 2B <input type="checkbox"/> W <input type="checkbox"/> 2W	<input type="checkbox"/> B <input type="checkbox"/> 2B <input type="checkbox"/> W <input type="checkbox"/> 2W	<input type="checkbox"/> B <input type="checkbox"/> 2B <input type="checkbox"/> W <input type="checkbox"/> 2W	<input type="text"/>
From the five options, please indicate your best option marking the box 'B'. Then, of the remaining four options, please indicates your worst option marking the box 'W'. Then, of the remaining three options, please indicates your second best option marking the box '2B'. Finally, from the remaining two options, please indicate your second worst option marking the box '2W'. In case you don't like any of the five options, please mark the option 'None'.						

**Figure 3** An example of a choice set presented in nonhypothetical best–worst scaling treatment.

it clear to participants that the money they would get at the end of the experiment is the monetary equivalent to the time they spend during the experiment and, hence, they have to perceive it as part of their disposal income and not as gifted money. Additionally, all participants were informed that they would be participating in nonhypothetical tasks which imply that respondents have to pay for of their most preferred olive oil at the end of the experiment. Therefore, it is in their best interest to reveal their actual preferences. Particularly, participants were shown how they can lose money if they deviate from their true valuations. Participants were then informed on how each CA format works. Participants in each treatment performed two choice tasks – a main task and a holdout task (see Appendix S1).

In the main task, participants were successively provided with nine choice sets – first, they received the nine choice sets obtained in the efficient design; then, they received the fifth choice set again to help assess the consistency of their responses. In each choice set, participants were asked to mark their most-preferred product concept, or to rank all the product concepts, or to choose the best and the worst product concepts, depending on the treatment (NHCE, NHRCA or NHMBWS).

In the holdout task, participants were given a single choice card of 10 product concepts, which are different from the product concepts provided to participants in the main task, plus a no-choice option (Figure 4). Then, they



Identification number: .....						
	Olive oil 1	Olive oil 2	Olive oil 3	Olive oil 4	Olive oil 5	Option 'No buy'
Type of olive oil	Extra virgin	Virgin	Olive oil	Extra virgin	Virgin	None  of the  ten olive oils
Brand	Private	Private	Private	Manufacturer	Private	
Origin	Andalucia	Andalucia	Catalonia	Catalonia	Rest of Spain	
Price (€)	3.50	2.20	4.80	3.50	4.80	
	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
	Olive oil 6	Olive oil 7	Olive oil 8	Olive oil 9	Olive oil 10	
Type of olive oil	Olive oil	Virgin	Extra virgin	Virgin	Olive oil	
Brand	Private	Manufacturer	Manufacturer	Manufacturer	Manufacturer	
Origin	Rest of Spain	Catalonia	Rest of Spain	Andalucia	Andalucia	
Price (€)	3.50	2.20	2.20	4.80	3.50	
	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
Please mark the olive oil you would purchase or mark the option 'No buy' if you are not willing to purchase any the ten olive oils.						

Figure 4 Example of a choice set presented in the Holdout task (training session).

were asked to choose the product concept they prefer most among the 10 product concepts included in the choice set.

Each of the three treatments (NHCE, NHRCA and NHMBWS) was conducted in five sessions throughout different days of the week and different hours of the day. Ten to fifteen subjects participated in each session. After finishing the two tasks, participants were asked to complete a short questionnaire about their sociodemographic and lexicographic characteristics, as well as their attitudes towards olive oil.

2.1.1 Nonhypothetical discrete choice experiment

In the NHCE treatment, participants were informed that each choice set was a real shopping scenario. In each choice set, participants were asked to indicate the product concept they preferred most, bearing in mind their real purchase habits. Therefore, at the end of the experiment each participant was given the product concept they had selected (if different from the no-choice option) and then paid its price. After finishing the main task, participants were given a choice set of 11 options, that is 10 product concepts and the no-choice option, and they were asked to choose the product concept they preferred most.

After completing the two tasks and the questionnaire, a volunteer among the participants was asked to randomly draw one of the two tasks to be the binding task. If the binding task was the main task, another volunteer was selected to randomly draw one of the nine choice sets<sup>3</sup> to determine which of

<sup>3</sup> The last choice set (the number 10) was the same as the fifth choice set. Therefore, to allow that all the choice sets have the same probability to be drawn we removed the tenth choice set.

the choice set was the binding one. Then, each participant was provided with the product concept they had chosen in the binding choice set and received 15 Euros minus the price of the chosen product concept. If the participant chose the no-choice option, they received the 15 Euros and did not buy any product. If the binding task was the holdout task, each participant was given the chosen product concept and was asked to pay its price. Furthermore, if the chosen option was the no-choice option, the participant received 15 Euros and did not buy any product.

### *2.1.2 Nonhypothetical rank conjoint analysis*

The same 10 choice sets that were provided in the NHCE treatment were successively presented to participants in the NHRCA treatment. However, in this treatment they were asked to rank the five product concepts included in each choice set from the most to the least-preferred product concept. In case, a participant does not like any one of the five product concepts, and they have to mark the no-choice option. The nonhypothetical nature of the experiment was also revealed to participants before performing the ranking task. After completing all of the choice sets in the main task, participants were given a choice set of 11 options, that is a holdout task, and were then asked to choose the product concept they preferred most or mark the no-choice option.

After completing the main and holdout tasks, a volunteer among the participants was asked to randomly draw one of the two tasks to be the binding task. If the main task was chosen as the binding task, another volunteer would be approached to draw the binding choice set. As in Lusk *et al.* (2008), the nonhypothetical nature of the RCA requires each participant purchases the binding product with a probability proportional to the rank they assign to each one of the five product concepts. Particularly, each participant who did not choose the no-choice option was asked to draw a number from 1 to 50 to select the binding product. If the drawn number was between 1 and 17, the participant would purchase the most-preferred product concept and would pay its price. If the drawn number was between 18 and 30, the second most preferred option would be the bidding product. If the drawn number was between 31 and 40, the participant would purchase the product concept they ranked third. If the number drawn was between 41 and 47, the participant would buy their fourth most-preferred product concept. If the drawn number was between 48 and 50, the participant would have to buy the product concept they ranked fifth. Finally, if the binding task was the holdout task, the procedure implemented was similar to the one used in NHCE treatment.

### *2.1.3 Nonhypothetical multiprofile best–worst scaling*

In nonhypothetical multiprofile best–worst scaling (NHMBWS), each participant was asked to mark the best product concept, that is the most-preferred product concept, followed by the worst product concept, that is the least-preferred product concept of the four remaining options, followed by

the second-best product concept of the three remaining options, and finally the second-worst product concept of the two remaining options. As a result, a complete ranking of the five product concepts can be deduced, that is the product concept ranked first, second, third, fourth and fifth are the best, the second best, the remaining product concept, the second worst and the worst product concept, respectively.

After finishing the main task and similar to the other two treatments (NHCE and NHRCA), participants in NHMBWS were given a choice set of 11 product concepts, that is a holdout task, and were asked to choose the product they preferred most. Once participants finished the main and holdout tasks, a similar procedure to the one applied in the NHRCA was used to determine the binding task, the binding choice set and the product that the participant must purchase and the price they have to pay.

## 2.2 Data analysis

### 2.2.1 Estimation of partworths

Participants' choice decisions made in any of the three CA formats considered in this paper are analysed using random utility theory (McFadden 1973). The random utility theory postulates that the  $i^{\text{th}}$  individual's utility function,  $U_{ijs}$ , towards an option  $j$  from a choice set  $s$  can be decomposed into a systematic (observable) component,  $V_{ijs}$ , and a stochastic (nonobservable) component,  $\varepsilon_{ijs}$ . The utility of the  $i$ th individual is given by:

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

The systematic component is typically assumed to be a linear relationship of observed attribute levels and respondents' characteristics. In the case of this study, the systematic component is specified as follows:

$$V_{ijs} = \beta_0 \text{No Buy} + \beta_{\text{EVOO}} \text{EVOO}_{ijs} + \beta_{\text{OO}} \text{OO}_{ijs} + \beta_{\text{Manf}} \text{Manf}_{ijs} + \beta_{\text{CAT}} \text{CAT}_{ijs} \\ + \beta_{\text{RSp}} \text{RSp}_{ijs} + \beta_{\text{price}} \text{price}_{ijs}. \quad (2)$$

The attribute levels, that is extra virgin olive oil (EVOO), olive oil (OO), manufacturer label (Manf), Catalonian origin (CAT) and the 'Rest of Spain' origin (RSp), were effect coded ( $-1, 0, 1$ ),<sup>4</sup> except for the price that was coded as a linear variable. The parameter 'No Buy' 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 random parameter logit model (RPL) was used to estimate the partworths

<sup>4</sup> The attribute levels virgin olive oil (VOO), private label (PRV) and Andalusia (AND) were set as the baseline levels for the attributes: type of olive oil, brand and origin, respectively.

( $\beta_0$ ,  $\beta_{\text{EVOO}}$ ,  $\beta_{\text{OO}}$ ,  $\beta_{\text{Manf}}$ ,  $\beta_{\text{CAT}}$ ,  $\beta_{\text{RSp}}$  and  $\beta_{\text{price}}$ ). RPL controls for preference heterogeneity among respondents by allowing one or more of the parameters in the model to be randomly distributed. It also relaxes the assumption of independence of the alternatives considered in a choice set by allowing the unobserved factors to be correlated over time (McFadden and Train 2000).

In the RPL, the unconditional probability that consumer  $i$  chooses the option  $j$  in the choice set  $s$  is given by Train (2003):

$$\text{Prob}_i(j \text{ is chosen}) = \int L_{ij}(\beta_{ij}) f(\beta_i/\theta) d\beta_i, \quad (3)$$

where  $f(\beta_i/\theta)$  is the density function of the coefficients  $\beta_i$ .  $\theta$  represents the moments (the mean and standard deviation) of the parameters' distributions, and  $L_{ij}(\beta_{ij})$  is the conditional probability that individual  $i$  chooses the option  $j$ .  $L_{ij}(\beta_{ij})$  is given by:

$$L_{ij}(\beta_{ij}) = \frac{e^{V_{ij}}}{\sum e^{V_{ik}}} = \frac{e^{\beta_{ij}X_{ij}}}{\sum e^{\beta_{ik}X_{ik}}}, \text{ with } k \in C_s. \quad (4)$$

In the case of the 'choice' data obtained in the NHRCA and NHMBWS treatments, the partworths were estimated using the rank-order RPL model (Lusk *et al.* 2008). The RO-RPL 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 modelled 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:

$$L_{ij}(\text{ranking } A, B, C, D, E) = \frac{e^{V_{iA}}}{\sum_{j=A,B,C,D,E} e^{V_{ij}}} \times \frac{e^{V_{iB}}}{\sum_{j=B,C,D,E} e^{V_{ij}}} \times \frac{e^{V_{iC}}}{\sum_{j=C,D,E} e^{V_{ij}}} \times \frac{e^{V_{iD}}}{\sum_{j=D,E} e^{V_{ij}}}. \quad (5)$$

In the estimation of RPL and RO-RPL, it was assumed that all the partworths,  $\beta_{ij}$ , of our empirical model were random and followed a normal distribution with mean  $\beta$  and variance–covariance matrix  $\Omega$ .

Since this study aims to compare participants' preferences and WTP across treatments (between-subjects analysis), it is important to investigate the

preference regularity across treatments. Following Lusk and Schroeder (2004), the likelihood-ratio test was used to test the null hypothesis of the equality of preferences across treatments ( $\mu_{NHCE}\beta_{NHCE} = \mu_{NHRCA}\beta_{NHRCA}$ ) ( $\mu$  is the scale parameter). The likelihood-ratio test is calculated using the following expression:  $-2(LL_j - \Sigma LL_i)$ , which is distributed as a chi-square with  $K(M - 1)$  degrees of freedom.  $LL_j$  is the log likelihood values of the pooled data, for example pooling NHCE and NHRCA data, and  $LL_i$  is the log likelihood values of the estimated model for each treatment. Furthermore,  $K$  is the number of restrictions and  $M$  is the number of treatments (Swait and Louviere 1993; Louviere and Street 2000). If the hypothesis of partworths equality is rejected, then comparing the estimated partworths across treatments is appropriate. By contrast, if the hypothesis of partworths equality is accepted, then comparing the estimated partworths across treatments is not appropriate because the differences in the estimated partworths across treatments could be attributed to the difference in participants' preferences, or to the difference in the error variance, that is inverse of the scale parameter, across treatments or a combination of both.

The results of the likelihood ratio test are displayed in Table 1. The results show that the null hypothesis of preferences regularity is rejected even when the full ranking information is considered in the estimation of the partworths. Therefore, comparing the CA formats in terms of partworths is appropriate. To test the comparability of the estimated partworths across the treatments, the estimation procedure used by De-Magistris *et al.* (2013) was followed. First, the data were pooled that correspond to the treatments to be compared. Then, the extended utility function (see Eqn 6) was estimated as:

$$\begin{aligned}
 V = & \beta_0 \text{No Buy} + \beta_{\text{price}} \text{Price} + \beta_{\text{EVOO}} \text{EVOO} + \beta_{\text{OO}} \text{OO} + \beta_{\text{CAT}} \text{CAT} \\
 & + \beta_{\text{Manf}} \text{Manf} + \beta_{\text{RSp}} \text{RSp} + \gamma_{\text{NoBuy}} (\text{No Buy} \times \text{dtreat}) + \gamma_{\text{price}} (\text{price} \\
 & \times \text{dtreat}) + \gamma_{\text{EVOO}} (\text{EVOO} \times \text{dtreat}) + \gamma_{\text{OO}} (\text{OO} \times \text{dtreat}) + \gamma_{\text{CAT}} (\text{CAT} \\
 & \times \text{dtreat}) + \gamma_{\text{Manf}} (\text{Manf} \times \text{dtreat}) + \gamma_{\text{RSp}} (\text{RSp} \times \text{dtreat}) + \varepsilon,
 \end{aligned}
 \tag{6}$$

where *dtreat* is coded as '1' for the first treatment and '0' for the second treatment. For example, if NHCE and NHRCA are the treatments to be compared, *dtreat* is coded as '1' if the treatment is NHCE, and '0' if the treatment is NHRCA. In total, 10 extended utility functions were estimated. The significance and the signs of the estimated  $\gamma$  parameters were then used to test the comparability of the three CA formats in terms of the estimated partworths.

### 2.2.2 Willingness to pay

In addition to the estimation of partworths, choice data are often used to calculate WTP. WTP is commonly expressed as the negative ratio of the nonprice attribute coefficient to the price coefficient:

**Table 1** Results from preference regularity's tests

Test for preference regularity	Number of observations	Log likelihood	Likelihood ratio (LR)	Degrees of freedom	P-value
All treatments	8,910	-1,868.23			
NHCE	2,970	-591.45			
NHRRCA	2,970	-619.10			
NHRMBWS	2,970	-575.72			
H <sub>0</sub> : test of equality between nonhypothetical first choice option					
All treatments	5,940	-1,228.15	163.89	36	<0.005
NHRRCA	2,970	-619.10			
NHRMBWS	2,970	-575.72			
H <sub>0</sub> : test of equality between nonhypothetical NHRRCA and NHRMBWS					
All treatments	14,265	-3,457.67	66.64	12	<0.005
NHRCA	7,155	-1,745.57			
NHMBWS	7,110	-1,678.66			
H <sub>0</sub> : test of equality between nonhypothetical NHRCA and NHMBWS			66.87	12	<0.005

Note NHCE, nonhypothetical discrete choice experiment treatment; NHMBWS, nonhypothetical best-worst scaling treatment; NHRCA, nonhypothetical ranking conjoint analysis treatment; NHRMBWS, nonhypothetical best-worst scaling treatment recoded as a traditional discrete choice experiment; NHRRCA, nonhypothetical ranking conjoint analysis treatment recoded as a traditional discrete choice experiment.

$$WTP_{\text{nonprice attribute}} = - \frac{\beta_{\text{nonprice attribute}}}{\beta_{\text{price}}}. \quad (7)$$

Nonetheless, depending on the distributions of the coefficients, this standard approach of computing WTP can result in heavily skewed WTP distributions (Train and Weeks 2004). A common approach used to solve this problem is to specify the parameter price as fixed. However, it is often unreasonable to assume that all individuals have the same preferences for price (Meijer and Rouwendal 2006).

To get around this problem, Train and Weeks (2004) suggested to estimate the RPL in WTP space rather than in preference space. This is done by reformulating the model in such a way that the coefficients to be estimated represent the WTP measures and not the partworths. As a result, when the RPL is estimated in WTP space, the a priori assumptions about the distributions of the parameters are made on the WTP rather than on the parameters representing the partworths. The model in WTP space is given in Equation (8):

$$V = \beta_{\text{price}} \left[ \frac{\beta_0}{\beta_{\text{price}}} \text{No Buy} + \text{Price} + \frac{\beta_{\text{EVOO}}}{\beta_{\text{price}}} \text{EVOO} + \frac{\beta_{\text{OO}}}{\beta_{\text{price}}} \text{OO} + \frac{\beta_{\text{CAT}}}{\beta_{\text{price}}} \text{CAT} \right. \\ \left. + \frac{\beta_{\text{Manf}}}{\beta_{\text{price}}} \text{Manf} + \frac{\beta_{\text{RSp}}}{\beta_{\text{price}}} \text{RSp} \right] + \varepsilon. \quad (8)$$

Equation (8) can be rewritten as:

$$V = \beta_{\text{price}}[\theta_0 \text{No Buy} + \text{Price} + \theta_{\text{EVOO}} \text{EVOO} + \theta_{\text{OO}} \text{OO} + \theta_{\text{CAT}} \text{CAT} + \theta_{\text{Manf}} \text{Manf} + \theta_{\text{RSp}} \text{RSp}] + \varepsilon, \quad (9)$$

where  $\theta_i = \beta_i / \beta_{\text{price}}$  represents the estimated individuals' WTP.

To assess the comparability of the different CA formats in terms of participants' WTP, the estimation procedure used by De-Magistris *et al.* (2013) was followed again. The choice models were estimated, specifying the utility function as follows:

$$V = \beta_{\text{price}}[\theta_0 \text{No Buy} + \text{Price} + \theta_{\text{EVOO}} \text{EVOO} + \theta_{\text{OO}} \text{OO} + \theta_{\text{CAT}} \text{CAT} + \theta_{\text{Manf}} \text{Manf} + \theta_{\text{RSp}} \text{RSp}] + \gamma_{\text{EVOO}}(\text{EVOO} \times \text{dtreat}) + \gamma_{\text{OO}}(\text{OO} \times \text{dtreat}) + \gamma_{\text{cat}}(\text{CAT} \times \text{dtreat}) + \gamma_{\text{Manf}}(\text{Manf} \times \text{dtreat}) + \gamma_{\text{RSp}}(\text{RSp} \times \text{dtreat}) + \varepsilon, \quad (10)$$

where *dtreat* is coded as '1' for the first treatment and '0' for the second treatment.

### 2.2.3 Consistency and external validity

As mentioned previously, to assess participants' responses consistency across treatments, the fifth choice set was repeated at the end of the main task.<sup>5</sup> To measure the consistency of participants' responses in each treatment, the proportion of participants who gave the same response in the fifth and the 10th choice sets, that is the repeated choice sets, was calculated. The response was counted as a hit if it was found to be the same in the fifth and the 10th choice sets. Then, the hit rate was calculated by dividing the total number of hits by the total number of participants in each treatment. To compare the hit rates across treatments, the Z-test for independent samples was used. Finally, to assess the external validity of the estimates, the estimated partworths from the main task were used to predict participant responses in the holdout task. The predicted and the actual choice in the holdout task were compared to determine the hit rate. The Z-test for independent samples was used to compare the hit rates across treatments.

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<sup>5</sup> Brouwer *et al.* (2010) found that respondents were significantly more confident and certain about their choice at the end of the choice task than at the beginning. Therefore, we think that repeating the fifth choice set at the end of the choice task rather at the beginning could increase the reliability of the test.



**Table 2** Estimated partworths

Estimated parameters and standard deviations	Partial ranking information		Full ranking information		
	NHCE	NHRRCA	NHRMBWS	NHRCA	NHMBWS
Random parameters' estimates					
Extra virgin olive oil (EVOO)	0.925***	0.794***	0.988***	0.665***	0.687***
Olive oil (OO)	-1.021***	-0.883***	-0.876***	-0.728***	-0.656***
Manufacturer label (Manf)	0.213**	0.158**	0.187**	0.131**	0.145***
Catalonia (CAT)	0.911***	0.553***	0.940***	0.274***	0.612***
Rest of Spain (RSp)	-0.577***	-0.666***	-0.545***	-0.424***	-0.639***
Price	-1.213***	-0.697***	-1.089***	-0.447***	-0.834***
No Buy	-3.340***	-5.050***	-5.015***	-4.641***	-4.437***
Standards deviations of the random parameters					
EVOO	1.772***	1.460***	2.195***	1.048***	1.129***
OO	1.715***	1.365***	2.638***	0.930**	1.324***
Manf	0.283**	0.224**	0.410**	0.350***	0.156***
CAT	1.329***	0.689***	1.143***	0.630***	0.597***
RSp	0.992***	0.502**	0.639***	0.596***	0.489***
Price	0.497***	1.153***	1.128***	0.945***	0.894***
Number of observations	2,970	2,970	2,970	7,155	7,110
Log-likelihood	-591.455	-619.106	-575.723	-1,745.575	-1,678.663
Log-likelihood ratio	283.08	287.53	308.24	899.49	896.86

Note \*\*\* and \*\* denote statistical significance at 1% and (5%) level, respectively. NHCE, nonhypothetical discrete choice experiment treatment; NHMBWS, nonhypothetical best-worst scaling treatment; NHRCA, nonhypothetical ranking conjoint analysis treatment; NHRMBS, nonhypothetical best-worst scaling treatment recorded as a discrete choice experiment; NHRRCa, nonhypothetical ranking conjoint analysis treatment recorded as a discrete choice experiment.

### 3 Results and discussion

#### 3.1 Partworths

The means and the standard deviations of the estimated partworths in the different treatments are displayed in Table 2. In the first three columns of Table 2, we report the estimated partworths in NHCE, NHRCA and NHRMBWS, where only the information on the most-preferred option is considered in the estimation of the partworths. The results displayed in the last two columns of Table 2 are from the estimation of RO-RPL, that is in NHRCA and NHMBWS, taking into account the full ranking information.

The results show that participants' preferences across CA formats were comparable in terms of the sign and significance of the estimated partworths. For instance, the results show that participants in all the treatments were more (less) likely to choose extra virgin (virgin) olive oil than non-virgin olive oil. Participants were also found to prefer manufacturer label over private label and local (Catalonia) olive oil over nonlocal olive oil (olive oil from Andalusia or the rest of Spain). Furthermore, the results show that participants in the different treatments preferred the attribute price to take lower levels (cheaper olive oils are generally preferred). Finally, the negative and significant sign of the 'No Buy' coefficient shows that respondents preferred to buy olive oil rather than opting out and choosing the no-choice option. All the estimated standard deviations were statistically significant, showing that participants' preferences in all the treatments were heterogeneous.

Although the estimates from the five models have the same signs, some differences in the means and standard deviations of the partworths can be noticed. As previously mentioned, the procedure used by De-Magistris *et al.* (2013) was followed to test whether the differences in the partworths' values are statistically significant. The results of the estimated coefficients ( $\gamma$ ) that correspondent to the variables 'dtreat<sub>x</sub>' (e.g. dtreat<sub>NHCE</sub>) are displayed in Tables 3 and 4. The results show that when only the information on the most-preferred option is considered in the estimation of the partworths (see Table 3), few statistically significant differences are detected. Particularly, five out of 21 estimated partworths were statistically different across the treatments – NHCE, NHRCA and NHRMBWS. Nonetheless, when the full ranking information is considered in the estimation of the partworths, we found that 16 out of 49 estimated partworths were statistically different across treatments.

These aforementioned findings are in line with the findings of Louviere *et al.* (2008); Lusk *et al.* (2008); Chang *et al.* (2009) and Lancsar *et al.* (2013), who showed that considering the additional information collected in RCA and BWS in the estimation of the partworths is likely to lead to different

**Table 3** Hypothesis test of equality of preferences parameters across the treatments taking into account only information on the most preferred option

Treatments	Variables	Estimated $\gamma$
NHCE vs. NHRRCA	$NOP \times dtreat_{NHCE}$	0.695
	$EVOO \times dtreat_{NHCE}$	0.177
	$OO \times dtreat_{NHCE}$	-0.164
	$Manf \times dtreat_{NHCE}$	-0.047
	$CAT \times dtreat_{NHCE}$	0.358*
	$RSp \times dtreat_{NHCE}$	0.089
	$Price \times dtreat_{NHCE}$	-0.716***
NHCE vs. NHRBWS	$NOP \times dtreat_{NHCE}$	1.039**
	$EVOO \times dtreat_{NHCE}$	0.065
	$OO \times dtreat_{NHCE}$	-0.273
	$Manf \times dtreat_{NHCE}$	0.042
	$CAT \times dtreat_{NHCE}$	0.183
	$RSp \times dtreat_{NHCE}$	-0.029
	$Price \times dtreat_{NHCE}$	-0.164
NHRRCA vs. NHRBWS	$NOP \times dtreat_{NHRRCA}$	-0.043
	$EVOO \times dtreat_{NHRRCA}$	-0.398
	$OO \times dtreat_{NHRRCA}$	0.112
	$Manf \times dtreat_{NHRRCA}$	0.003
	$CAT \times dtreat_{NHRRCA}$	-0.400**
	$RSp \times dtreat_{NHRRCA}$	-0.082
	$Price \times dtreat_{NHRRCA}$	0.310*

Note \*\*\*, \*\* and \* denote statistical significance at (1%), (5%) and (10%) level, respectively. NHCE, nonhypothetical discrete choice experiment treatment; NHRBWS, nonhypothetical best–worst scaling treatment recoded as a discrete choice experiment; NHRRCA, nonhypothetical ranking conjoint analysis treatment recoded as a discrete choice experiment.

estimates than those obtained in CE. Furthermore, Akaichi *et al.* (2013) did not find differences between NHCE and NHRRCA in terms of the estimated partworths when the choice sets provided to respondents were small (four alternatives); however, they found discrepancies between respondents' partworths in NHCE and NHRRCA when large choice sets (eight alternatives) were used.

Furthermore, the results show that in four out of ten cases the coefficient associated with no-purchase option was significant. Hence, it is worth noting that the participants recruited in RCA and MBWS treatments likely have more tendencies to choose between the presented product concept than the no-purchase option than the participants of CE.

### 3.2 Response consistency and external validity

Results from response consistency and external validity analyses are reported in Table 5. In general terms, the consistency of participants' responses is relatively high in the three CA formats. The hit rate ranges from 76.36 per cent to 78.18 per cent when only the most preferred option is considered in the estimation. Results from the one-tailed Z-test show that the differences

**Table 4** Hypothesis test of equality of preferences parameters across the treatments taking into account the full ranking information

Treatments	Variables	Estimated $\gamma$
NHRCA vs. NHCE	$NOP \times dtreat_{NHRCA}$	-0.978**
	$EVOO \times dtreat_{NHRCA}$	0.210
	$OO \times dtreat_{NHRCA}$	-0.306**
	$Manf \times dtreat_{NHRCA}$	-0.100
	$CAT \times dtreat_{NHRCA}$	-0.447***
	$RSp \times dtreat_{NHRCA}$	0.139
	$Price \times dtreat_{NHRCA}$	0.605***
NHBWS vs. NHCE	$NOP \times dtreat_{NHBWS}$	-0.715*
	$EVOO \times dtreat_{NHBWS}$	0.118
	$OO \times dtreat_{NHBWS}$	0.056
	$Manf \times dtreat_{NHBWS}$	-0.015
	$CAT \times dtreat_{NHBWS}$	0.075
	$RSp \times dtreat_{NHBWS}$	-0.192
	$Price \times dtreat_{NHBWS}$	0.358**
NHRCA vs. NHRCA	$NOP \times dtreat_{NHRCA}$	-0.185
	$EVOO \times dtreat_{NHRCA}$	-0.481**
	$OO \times dtreat_{NHRCA}$	0.304*
	$Manf \times dtreat_{NHRCA}$	-0.076
	$CAT \times dtreat_{NHRCA}$	0.051
	$RSp \times dtreat_{NHRCA}$	0.206
	$Price \times dtreat_{NHRCA}$	-0.250**
NHBWS vs. NHRCA	$NOP \times dtreat_{NHBWS}$	0.004
	$EVOO \times dtreat_{NHBWS}$	-0.441**
	$OO \times dtreat_{NHBWS}$	0.644***
	$Manf \times dtreat_{NHBWS}$	-0.017
	$CAT \times dtreat_{NHBWS}$	0.182
	$RSp \times dtreat_{NHBWS}$	0.084
	$Price \times dtreat_{NHBWS}$	-0.181
NHRCA vs. NHRBWS	$NOP \times dtreat_{NHRCA}$	-0.318
	$EVOO \times dtreat_{NHRCA}$	-0.125
	$OO \times dtreat_{NHRCA}$	-0.036
	$Manf \times dtreat_{NHRCA}$	-0.005
	$CAT \times dtreat_{NHRCA}$	-0.205
	$RSp \times dtreat_{NHRCA}$	0.082
	$Price \times dtreat_{NHRCA}$	0.270**
NHBWS vs. NHRBWS	$NOP \times dtreat_{NHBWS}$	0.613
	$EVOO \times dtreat_{NHBWS}$	0.229
	$OO \times dtreat_{NHBWS}$	-0.396
	$Manf \times dtreat_{NHBWS}$	-0.009
	$CAT \times dtreat_{NHBWS}$	-0.117
	$RSp \times dtreat_{NHBWS}$	-0.024
	$Price \times dtreat_{NHBWS}$	0.437***
NHRCA vs. NHBWS	$NOP \times dtreat_{NHRCA}$	-0.716*
	$EVOO \times dtreat_{NHRCA}$	0.210**
	$OO \times dtreat_{NHRCA}$	-0.364***
	$Manf \times dtreat_{NHRCA}$	0.041
	$CAT \times dtreat_{NHRCA}$	-0.125
	$RSp \times dtreat_{NHRCA}$	0.034
	$Price \times dtreat_{NHRCA}$	-0.066

Note \*\*\*, \*\* and \* denote statistical significance at (1%), (5%) and (10%) level, respectively. NHCE, nonhypothetical discrete choice experiment treatment; NHBWS, nonhypothetical best–worst scaling treatment; NHRCA, nonhypothetical ranking conjoint analysis treatment; NHRBWS, nonhypothetical best–worst scaling treatment recoded as a discrete choice experiment; NHRCA, nonhypothetical ranking conjoint analysis treatment recoded as a discrete choice experiment.

**Table 5** Consistency and external validity tests

Treatments (Treatment1 vs. Treatment2)	Consistency (hit rate (%))			External validity (hit rate (%))		
	Treatment1	Treatment2	P-value	Treatment1	Treatment2	P-value
NHCE vs. NHRRCa	78.18	76.36	0.41	43.63	38.18	0.28
NHCE vs. NHRMBWS	78.18	76.36	0.41	43.63	52.72	0.17
NHCE vs. NHRCA	78.18	49.09	0.00	43.63	40.00	0.35
NHCE vs. NHMBWS	78.18	45.45	0.00	43.63	61.81	0.03
NHRRCa vs. NHRMBWS	76.36	76.36	0.50	38.18	52.72	0.06
NHRRCa vs. NHRCA	76.36	49.09	0.00	38.18	40.00	0.42
NHRRCa vs. NHMBWS	76.36	45.45	0.00	38.18	61.81	0.00
NHRMBWS vs. NHRCA	76.36	49.09	0.00	52.72	40.00	0.90
NHRMBWS vs. NHMBWS	76.36	45.45	0.00	52.72	61.81	0.17
NHRCA vs. NHMBWS	49.09	45.45	0.35	40.00	61.81	0.01

between NHCE, NHRRCa and NHRMBWS in terms of response consistency are not statistically significant. Nonetheless, when the full ranking information was considered in the estimation of the partworths, the consistency's hit rate decreased significantly to 49.09 per cent and 45.45 per cent, in NHRCA and NHMBWS, respectively. This phenomenon could be explained by the fact that the stability of the ranking information decreased when the number of options to be ranked increased, due to the higher cognitive effort spent in RCA and BWS in ranking all the different product concepts (Ben-Akiva *et al.* 1992).

The consistency of participant responses was found to be similar between NHRCA and NHMBWS. Therefore, the way respondents are asked to rank the different options in a choice set that does not appear to alter consistency of their responses in NHRCA and NHMBWS. According to Boxall *et al.* (2009), this could be attributed to similarity of sociodemographic characteristics of respondents across treatments samples. Furthermore, the results in Table 5 show that response consistency is significantly lower in NHRCA and NHMBWS than in NHCE. This result implies that in nonhypothetical settings, CE performs better in terms of response consistency than RCA and BWS. As highlighted by Ben-Akiva *et al.* (1992) and Chapman and Staelin (1982), the respondents may assign less attention to ranking inferior alternatives and find it more natural to choose the most preferable alternative than assign ranks to all alternatives.

Regarding the external validity, the results show that the estimated partworths accurately predicted between 38.18 per cent and 61.81 per cent of participant responses in the holdout task across the treatments. Consistent with the findings of Akaichi *et al.* (2013), we found that when only information on the most-preferred/ranked first product concept was used in the estimation of partworths, the external validity in the nonhypothetical choice and ranking CA formats (NHCE, NHRCA and NHRMBWS) is similar. Notably, the most striking result in our study is when the full ranking information is considered in the estimation of partworths, the external validity is significantly higher in NHMBWS than in NHRCA and NHCE. The additional information gained from ranking of all the options in each choice set and the easier handling of NHMBWS by respondents in comparison with NHRCA (Marley and Louviere 2005; Vermeulen *et al.* 2010; Potoglou *et al.* 2011; Flynn and Marley 2014) are probably the reasons behind the superiority of NHMBWS in terms of external validity. In fact, the best and the last preferable alternatives are easier to identify by the respondents and consequently the information associated to identify the extremes have less noise than traditional rank task leading to significant differences on stated preferences data reliability between treatments (Ben-Akiva *et al.* 1992).

Certainly, more research is needed to confirm our finding and explain the sources of the differences and the similarities between the three CA formats in terms estimated partworths and external validity.

### 3.3 Willingness to pay

One of the main reasons for using DCEs is to estimate consumers' WTP for specific food attributes. Therefore, we also assessed the comparability of the three CA formats in terms of respondents' WTP. The results that correspond to the estimated WTP space are displayed in Table 6. These results show that the sign and the significance of the estimated WTP are similar across the three CA formats. Particularly, we found that participants in the three treatments were willing to pay a price premium for EVOO. This confirms the results of Bernabéu *et al.* (2009) who found that Spanish consumers are willing to pay, on average, 13 per cent for the EVOO over the conventional olive oil. Furthermore, in line with Yanguí *et al.* (2014), the results also show that respondents were willing to pay more for olive oil with manufacturer label and local olive oil than olive oil with private label and nonlocal olive oil. In all the treatments, participants were found to value the type of olive oil more than its origin, which in turn was more valued than the brand of olive oil (manufacturer vs. private). Importantly, all the standard deviations were statistically significant, implying that participants' WTP were heterogeneous.

The results displayed in Table 6 show some differences across treatments in terms of estimated WTP; for example, the price premium for the EVOO is 0.98€ in NHCE and 1.95€ in NHRCA, despite the similarity of the

**Table 6** Estimated willingness to pay space in the different treatments

Estimated parameters and standard deviations	Partial ranking information			Full ranking information	
	NHCE	NHRRCA	NHRMBWS	NHRCA	NHMBWS
Random parameters' estimates					
Extra virgin olive oil (EVOO)	0.989***	1.959***	1.495***	1.351***	1.052***
Olive oil (OO)	-0.854***	-2.125***	-1.444***	-1.579***	-0.949***
Manufacturer label (Manf)	0.200**	0.372**	0.211*	0.394**	0.236***
Catalonia (CAT)	0.760***	0.678***	0.945***	1.032***	0.880***
Rest of Spain (RSp)	-0.563***	-1.150***	-0.807***	-1.290***	-0.978***
Standards deviations of the random parameters					
EVOO	1.684***	2.560***	2.065***	3.278***	2.133***
OO	1.650***	2.531***	2.404***	2.728***	2.592***
Manf	0.316**	0.625**	0.436**	1.168***	0.471***
CAT	1.257***	1.406***	1.076***	1.555***	1.127***
RSp	0.816***	1.132***	0.570***	1.391***	1.033***
Number of observations	2,970	2,970	2,970	7,155	7,110
Log-likelihood	-627.716	-702.480	-642.333	-1,983.443	-1,921.410

Note \*\*\*, \*\* and \* denote statistical significance at 1%, (5%) and (10%) level, respectively. NHCE, nonhypothetical discrete choice experiment treatment; NHMBWS, nonhypothetical best–worst scaling treatment; NHRCA, nonhypothetical ranking conjoint analysis treatment; NHRMBWS, nonhypothetical best–worst scaling treatment recoded as a discrete choice experiment; NHRRCA, nonhypothetical ranking conjoint analysis treatment recoded as a discrete choice experiment.

estimates' sign and statistical significance. Furthermore, we estimated all the interactions between each one of the nonprice attributes and a dummy variable that controls for treatment effect to test whether these apparent differences across the various CA formats were statistically significant. The results are displayed in Tables 7 and 8, showing that when only the information on the most-preferred option is considered in the estimation of participants' WTP (see Table 7), then only one out 15 estimated WTP was statistically different across the treatments (NHCE, NHRRCA and NHRMBWS). These results corroborate those of Akaichi *et al.* (2013) who found that participants in NHCE and NHRRCA had statistically similar WTP, even when large choice sets were used; likewise, Caparrós *et al.* (2008) found similar results.

Interestingly, the results reported in Table 8 show that when the full ranking information is considered in the estimation of participants' WTP, then only five out of 35 estimated WTP values were statistically different across treatments. Indeed, in some situations, when the respondents were



**Table 7** Hypothesis test of equality willingness to pay values across the treatments taking into account only information on the most preferred option

Treatments	Variables	Estimated $\gamma$
NHCE vs. NHRRCA	$EVOO \times dtreat_{NHCE}$	-0.624
	$OO \times dtreat_{NHCE}$	1.093**
	$Manf \times dtreat_{NHCE}$	-0.039
	$CAT \times dtreat_{NHCE}$	0.481
	$RSp \times dtreat_{NHCE}$	0.228
NHCE vs. NHRMBWS	$EVOO \times dtreat_{NHCE}$	-0.467
	$OO \times dtreat_{NHCE}$	0.326
	$Manf \times dtreat_{NHCE}$	-0.008
	$CAT \times dtreat_{NHCE}$	-0.183
	$RSp \times dtreat_{NHCE}$	0.234
NHRRCA vs. NHRMBWS	$EVOO \times dtreat_{NHRRCA}$	-0.243
	$OO \times dtreat_{NHRRCA}$	-0.339
	$Manf \times dtreat_{NHRRCA}$	0.060
	$CAT \times dtreat_{NHRRCA}$	-0.481
	$RSp \times dtreat_{NHRRCA}$	-0.070

Note \*\* denote statistical significance at (5%) level, respectively. NHCE, nonhypothetical discrete choice experiment treatment; NHRMBWS, nonhypothetical best–worst scaling treatment recoded as a discrete choice experiment; NHRRCA, nonhypothetical ranking conjoint analysis treatment recoded as a discrete choice experiment.

very familiar with the products and its attributes, as in our case the olive oil for Spanish consumers, they consistently know their preferences and their stated preferences could be influenced by their current actual choices leading for a similarity in consumers' perception and their willing to pay (Brouwer *et al.* 2010).

None of the previous studies, that compared different CA formats and considered the full ranking information in the estimation of the parameters, assessed the comparability of the CA formats in terms of participants' WTP. Future research could potentially answer the question of why NHCE, NHRRCA and NHMBWS produce different partworths and have different external validities, but are comparable in terms of estimated WTP.

#### 4 Conclusions

Consumers' preferences and WTP for private and public goods are increasingly quantified using different conjoint analysis formats such as DCE, RCA and BWS. The empirical comparison of these preference and value-elicitation methods is important because the three different approaches have strengths and weaknesses – neither can be ruled out a priori as inferior. This study expands the work of previous studies by assessing the comparability of DCE, RCA and MBWS when used in nonhypothetical settings.

Our results show that the three CA formats provide similar results in terms of the sign and significance of estimated partworths, as well as the estimated WTP values, in almost all cases independently of whether the

**Table 8** Hypothesis test of equality willingness to pay values across the treatments taking into account the full ranking information

Treatments	Variables	Estimated $\gamma$
NHRCA vs. NHCE	$EVOO \times dtreat_{NHRCA}$	0.319
	$OO \times dtreat_{NHRCA}$	-0.826**
	$Manf \times dtreat_{NHRCA}$	0.072
	$CAT \times dtreat_{NHRCA}$	-0.399
	$RSp \times dtreat_{NHRCA}$	-0.345
NHMBWS vs. NHCE	$EVOO \times dtreat_{NHMBWS}$	-0.335
	$OO \times dtreat_{NHMBWS}$	0.308
	$Manf \times dtreat_{NHMBWS}$	-0.049
	$CAT \times dtreat_{NHMBWS}$	-0.312
	$RSp \times dtreat_{NHMBWS}$	-0.034
NHRCA vs. NHRCA	$EVOO \times dtreat_{NHRCA}$	-0.258
	$OO \times dtreat_{NHRCA}$	0.065
	$Manf \times dtreat_{NHRCA}$	-0.221
	$CAT \times dtreat_{NHRCA}$	0.105
	$RSp \times dtreat_{NHRCA}$	0.380
NHMBWS vs. NHRCA	$EVOO \times dtreat_{NHMBWS}$	-0.856
	$OO \times dtreat_{NHMBWS}$	1.383***
	$Manf \times dtreat_{NHMBWS}$	-0.207
	$CAT \times dtreat_{NHMBWS}$	0.324
	$RSp \times dtreat_{NHMBWS}$	0.183
NHRCA vs. NHRMBWS	$EVOO \times dtreat_{NHRCA}$	-1.045**
	$OO \times dtreat_{NHRCA}$	0.259
	$Manf \times dtreat_{NHRCA}$	-0.168
	$CAT \times dtreat_{NHRCA}$	-0.765**
	$RSp \times dtreat_{NHRCA}$	0.234
NHMBWS vs. NHRMBWS	$EVOO \times dtreat_{NHMBWS}$	-0.143
	$OO \times dtreat_{NHMBWS}$	-0.202
	$Manf \times dtreat_{NHMBWS}$	-0.106
	$CAT \times dtreat_{NHMBWS}$	-0.110
	$RSp \times dtreat_{NHMBWS}$	0.034
NHRCA vs. NHMBWS	$EVOO \times dtreat_{NHRCA}$	-1.146***
	$OO \times dtreat_{NHRCA}$	0.613
	$Manf \times dtreat_{NHRCA}$	0.223
	$CAT \times dtreat_{NHRCA}$	-0.128
	$RSp \times dtreat_{NHRCA}$	-0.070

Note \*\*\* and \*\* denote statistical significance at (1%) and (5%) level, respectively. . NHCE, nonhypothetical discrete choice experiment treatment; NHMBWS, nonhypothetical best–worst scaling treatment; NHRCA, nonhypothetical ranking conjoint analysis treatment; NHRMBWS, nonhypothetical best–worst scaling treatment recoded as a discrete choice experiment; NHRCA, nonhypothetical ranking conjoint analysis treatment recoded as a discrete choice experiment.

partworths are estimated by considering only partial or full ranking information. Accordingly, our results suggest that if the estimation of consumers' WTP is the study's main objective, then using any one of the three CA formats would be appropriate. Particularly, the use of NHCE might be preferred because it is simpler to implement and it involves less cognitive burden for respondents, as compared to NHRCA and NHMBWS. Nonetheless, in the light of the fact that estimating both consumers' preferences and WTP is of great interest in the majority of

studies on consumer choice, our results suggest the use of NHMBWS over NHCE and NHRCA because it has a better predictive power of consumer preference and provides estimated WTP values that are similar to those obtained in the other CA formats.

As in any other empirical study, our work has some gaps that could be filled by future studies. For instance, more research is needed on the extent to which the comparability of the output obtained in NHCE, NHRCA and NHMBWS is affected by experimental design parameters such as the size and the number of choice sets, the sample size and the types of respondents and products. Specifically, further investigation is necessary into the sensitivity of our results to the effects of other factors such as the nonattendance of attributes (Chalak *et al.* 2016), participants' certainty about their choices (Rose *et al.* 2015) and the effect altruism and 'free riding' (Lusk and Shogren 2007).

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### Supporting Information

Additional Supporting Information may be found in the online version of this article:

**Appendix S1.** Instructions for participants in the three treatments.