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Analysis of choice inconsistencies in online choice experiments: impact on welfare measures

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Abstract

Individuals answering to choice experiments are assumed to behave in concordance with standard utility theory. However, empirical evidence finds that these assumptions are frequently violated, impacting on willingness to pay estimates. Because the cost attribute plays a key role in choice experiments used for environmental valuation, this study focuses on the impact of inconsistent choices with respect to cost on willingness to pay, drawing on data from a survey aimed at valuing the environmental and social impacts of organic farming in mountainous olive orchards. An iterative process is used to identify inconsistent choices. Results provide sufficient evidence to suggest that inconsistencies can considerably bias willingness to pay estimates. We propose that identifying and considering inconsistent choices enhances realism and accuracy of the conclusions drawn from choice experiments in environmental valuation.

Keywords:

Choice experiments, inconsistent choices, on-line survey, cost attribute

1. Introduction

Choice Experiments (CEs) have become a popular tool to provide guidance to policy makers about the value of environmental goods and services (Birol and Koundori, 2008; Bennett, 2011). In CEs, respondents are asked to choose the preferred alternative from a choice set, which typically contains between two and five alternatives. It is increasingly recognised that respondents to CE surveys frequently violate standard assumptions of rational utility maximising behaviour, which include evaluating each choice task independently and responding truthfully based on the complete set of information contained in choice tasks in a fully compensatory manner (Colombo and Glenk, 2014), while drawing on well-defined preferences that are invariant over the sequence of choice tasks (Day and Pinto-Prades, 2010). Consequently, much attention has recently been paid to account for various simplifying decision rules and information processing strategies in discrete choice models, and to analyse their impact on estimates of willingness to pay (WTP) (Adamowicz *et al.*, 2014).

Different information processing strategies and simplifying decision rules (heuristics) can be understood as a response of boundedly rational individuals, who adapt their response behaviour depending on context in choice environments (Payne *et al.*, 1993). In more complex choice situations, decision makers increasingly rely on the use of simplifying decision rules, because a full evaluation of all choice alternatives becomes increasingly costly for a respondent to process. Respondents therefore trade-off the benefits of additional efforts expended on a decision and the associated cognitive costs (Heiner, 1983). Beyond the complexity directly associated with the choice tasks *per se*, heuristics may be used if the environmental good itself has characteristics that are not clearly understood by respondents or if individuals are unfamiliar with the environmental good (Campbell *et al.*, 2008).

A range of conjunctive, disjunctive and lexicographic decision rules have been explored in the choice modelling literature (Swait, 2001; Hess *et al.*, 2012). Among the information processing strategies at the attribute evaluation stage, ‘attribute non-attendance’ has received much attention (for example, Campbell *et al.*, 2011; Colombo *et al.*, 2013; Alemu *et al.*, 2013; Glenk *et al*. 2014). This paper focuses on inconsistencies in respondents' choices with respect to the cost attribute[1], an issue which has received little attention in the literature despite potentially having a profound impact on CE outcomes. Inconsistent choices violate one or several of the axioms of rational choice behaviour[2]. The following is a typical example of an inconsistent choice with respect to the cost attribute that clearly violates the completeness and monotonicity axioms of a rational choice. A respondent declares to be willing to pay a maximum amount of € *X* for a specific environmental improvement. In the CE, however, s/he chooses alternatives that are associated with smaller environmental improvements at the same or at a larger cost. This may occur as a result of misunderstanding, boredom, fatigue, lack of interest, or because, given the hypothetical nature of the choice context, respondents allocate smaller importance to the cost associated with the environmental improvements (Cameron and DeShazo, 2010). Choices that violate axioms of rational choice behaviour may also be related to the elicitation method employed. Compared to responses to contingent valuation (CV) questions, responses to CEs may be more likely to reflect relative value rather than absolute value and therefore be more likely to violate individual budget constraints (Roe *et al*., 1996; Salensminde, 2003). Also, the experimental design may be the cause of choice inconsistencies if some respondents do not perceive the between-alternative difference in cost large enough to influence their choice, at least for a subset of the choice tasks (Puckett and Hensher, 2008). Another potential source of choosing inconsistently with respect to cost are anchoring effects resulting in choices that are dependent on cost values shown in preceding choice cards (Carlsson and Martinson, 2008; Ladenburg and Olsen, 2008; Mørkbak *et al.*, 2010). Finally, inconsistent choices may arise because of psychological constructs, such as ethical positions, environmental attitudes and social norms (Jones, 1998), or pro-social behaviour (Stern, 2000), which

[1] Choice inconsistencies may affect any attribute used in the choice cards. We focused on the cost attribute acknowledging its central importance in the estimation of the welfare measures.

[2] Individuals are assumed to hold rational preferences if these are complete, transitive, monotonic and continuous. Complete preferences mean that individuals know exactly what they prefer; transitive preferences mean that if good A if preferred to B and B to C, A is also preferred to C; monotonicity means that 'at least as much of everything is at least as good', i.e., respondents recognize dominant choices; continuity means that individuals are able to compensate the loss of one good by a gain of another (Ryan *et al.*, 2009).

drive respondents to choose the ‘policy-on’ alternatives regardless of their cost to avoid further environmental losses[3].

For a given respondent, it is difficult to establish the reasons for having chosen inconsistently given that the sources of inconsistency are likely to be varied and interconnected. Accordingly, choice inconsistencies may impact on both the random error in the choice process (DeShazo and Fermo, 2002; Fiebig *et al.*, 2010), and on individual systematic utilities (Dellaert *et al.*, 2012). The impact on the random term of utility is difficult to predict; individuals who systematically choose inconsistently, due to specific environmental attitudes, perceptions or social norms, may be ‘consistently inconsistent’ and as such have lower error variances. On the contrary, inconsistent choices which originate from preferences that are not well-formed as a consequence of unfamiliarity with the environmental good, lack of effort, inattention to the choice task or choice complexity are expected to result in greater error variances. The impact of choice inconsistencies on the systematic part of utility is clearer. If inconsistent choices related to the cost attribute are present, the marginal utility of income will be underestimated and welfare measures will be biased upwards[4]. As such, independently from the causes of choice inconsistencies, the message for policy makers who rely on the benefit estimates can be misleading. This paper aims to shed light on the importance of the inconsistent choices in CE, in particular on their effect on welfare measures. The specific objectives of this paper are threefold: first, to provide a procedure to detect inconsistent choices in CEs. Second, to explore the factors that may drive or influence the incidence of inconsistent choices. Third, to offer insights on the likely effects that may arise from different ways of treating inconsistent choices on WTP estimates. The results of this paper contribute methodologically to the literature by generating a procedure that identifies inconsistent choices that can be easily transferred to other studies and

[3] Note that this is different to ‘non-attendance’ to the cost attribute. In the case of inconsistent choices as defined in this paper, respondents are fully aware of the cost. Yet, for any reasons including aversion towards environmental degradation associated with choosing the *status quo* alternative, they still choose the alternative which provides an environmental improvement. Empirical work directly addressing the issue has found that a significant proportion of survey respondents treat the environment in a manner that is inconsistent with economic theory (Spash, 2006).

[4] This would not be the case if respondents carried out lexicographic choices with respect to the cost attribute by choosing always the cheapest alternative, neglecting all other attributes. This would result in an overestimation of the marginal utility of income and downscaled welfare measures.

contexts using stated preference methods. As pointed out by Salensminde (2006), analysts should use survey designs that collect more signal and less noise, and that can separate signal from noise. This requires a thorough investigation of each respondent's choices. The procedure described in this paper provides the analyst with the opportunity to examine challenging choices more thoroughly. Such choices tend to occur more frequently in environmental studies, where respondents are often not familiar with the goods and services investigated. The paper also contributes to the literature by providing evidence on the factors that explain choice inconsistencies. Finally, it provides evidence on the magnitude of difference in estimated welfare resulting from different considerations of how inconsistent choices should enter the modelling process. To the best of our knowledge, only one study that applied this procedure has been published in literature (Rocamora *et al*., 2014). The current study presents several advances over Rocamora *et al*. (2014): it analyses the factors which affect choice inconsistencies; it explicitly considers the random component of utility and the impact of inconsistent choices on it; it employs the cutoffs approach in the modelling stage; and finally, it compares estimates of open ended CV and CE elicitation formats.

We identify inconsistent choices with respect to the cost attribute for each respondent using a cutoffs approach. Different from previous studies that made use of price cutoffs (Bush *et al.*, 2009 or Ding *et al.*, 2010), respondents were given the opportunity to review and revise those choices that are found to be inconsistent with their stated price cutoff. This allowed not only resolving the inconsistent choices to make them consistent by using assumptions regarding acceptable thresholds of inconsistencies (Bush *et al*., 2009), but also to correct them based on the stated cutoff information provided by respondents.

In what follows, we first describe the design of the questionnaire and the CE (Section 2). Section 3 then summarizes the econometric approach employed for data analysis; results are reported in Section 4 and subsequently discussed (Section 5), followed by conclusions in Section 6.

2. Study design

The data for this study stems from a choice experiment aimed at investigating the welfare effects of implementing organic farming policies in mountainous olive orchards in Andalusia (South of Spain). Relative to conventional farming, organic farming in mountainous olive farming systems provides several non-market benefits to society that may require governmental support to safeguard their supply. In particular, organic farming in olive orchards reduces the carbon footprint of agriculture, improves agricultural biodiversity, reduces water pollution and soil erosion and is a source of employment and thus contributes to the viability of communities in rural areas.

The survey was carried out as an on-line questionnaire, a format which is increasing in its popularity in stated choice data collection due to, *inter alia*, reduced cost and faster completion times relative to mail, phone, and in-person surveys (Tomsor and Shupp, 2009). On-line questionnaires also make use of technological possibilities to provide respondents with a broader set of stimuli in terms of images and animated examples, to improve survey flow and to avoid data entry mistakes. As such, the on-line format is particularly convenient for valuing environmental goods that respondents are often not familiar with and that hence need to be carefully described in the questionnaire. However, on-line surveys are typically characterised by important limitations, especially regarding sample coverage and representativeness, self-selection bias and survey mode effects (Lindhem and Navrud, 2011a,b). In this study, the on-line implementation of the survey was a key aspect of the design of the questionnaire given that the lack of familiarity with both the choice experiment task and the issue investigated in the study may be sources of choice inconsistency. The environmental and social effects of organic farming were introduced to respondents through short and clear pieces of information in order to keep their attention. Images and graphical illustrations were accompanied by plain language descriptions and explanations, all of which were thoroughly pre-tested in focus groups and individual interviews for understanding[5]. The CE task was carefully explained to respondents, who were reminded of the implicit need to trade off the benefits of the 'policy-on' alternatives with

[5] Two focus groups and several individual interviews with citizens were carried out before launching the on-line survey. Additionally, a pre-test of 30 on-line surveys was performed.

their associated cost. Furthermore, respondents were also offered the possibility of viewing examples of completed choice tasks with explanations of the trade-offs involved in choosing. In order to ease the comprehension of the attributes and levels, we captured this information in one simple table, which was made always available throughout the completion of the choice tasks through a simple click.

Six choice cards were presented to each respondent, who were asked to choose the preferred alternative from three alternatives, as shown in Figure 1. The first alternative was held constant across choice tasks and described the current situation of olive grown mountain areas according to the selected attributes. The remaining two alternatives varied between choice cards.

Figure 1: Example of a typical choice card

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Prior to the CE, the interviewees were reminded about their budget constraint and the existence of alternative goods they may prefer to consume. In order to encourage respondents to think carefully about their budget constraint, we delayed the availability of the following page of the survey for thirty seconds, emphasizing the importance of the information shown for carrying out the subsequent choice tasks.

The procedure used to identify and reconsider inconsistent responses directly followed the CE exercise. All respondents who chose a 'policy-on' alternative at least once were inquired about their maximum WTP for the 'best' possible scenario according to the attribute levels. This was accomplished by showing respondents a choice card, on which we paired the *status quo* with an alternative that was defined by the attribute levels representing the largest environmental and social improvements. This alternative was superior in terms of utility to any of the alternatives shown in the choice cards, given that none of the alternatives used in the CE incorporated the 'best' possible scenario according to all non-cost attributes. To ensure that the stated WTP was a close proxy of the maximum amount they were willing to pay, respondents were again reminded to consider their budget constraint before asking them to state the maximum amount of money they are willing to pay in exchange for the scenario shown. We also emphasized that the stated WTP must be the amount of money above which they would not be willing to pay even a single cent more.

Choices were classified as inconsistent if the maximum WTP stated by respondents for the ‘best’ scenario was lower than the cost associated with a chosen alternative in the CE exercise. Respondents with choice tasks identified to be inconsistent were informed about their inconsistency and given the opportunity to reconsider their choices in these tasks (Figure 2). It is important to note that we did not prompt them to change their initial choice, but simply asked them to either confirm or revise it.

Figure 2: The iterative procedure to detect choice inconsistencies.

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Throughout the survey, we recorded information about the time spent by each respondent on different sections of the questionnaire. In particular, we observed the total time each respondent dedicated to the reading of the information provided, and the time spent on the choice tasks. The panel members received a reward for each completed survey. Given this incentive structure, concerns are justified that respondents might want to answer the survey as quickly as possible, or complete it discontinuously during short breaks to simply receive the reward. In the literature there are no clear directional expectations with respect to the overall effect of individual differences in total decision time[6], which can vary greatly across individuals. However, the presence of *extremely* short or long response times can signal anomalies in carrying out the survey and should therefore alert analysts about possible problems with the stated choices. These indicators were used as proxies, together with a set of demographic variables, to test whether there is a systematic relationship between time taken to

[6] Longer decision time can either indicate lower cognitive capability, be a signal of greater involvement in the choice task (Otter *et al*., 2008), or be an indicator of a more ‘relaxed’ approach to responding (Bonsall and Lythgoe, 2009). Alternatively, longer decision times have been associated with more complex choice tasks (Dellaert *et al*., 2012), and with respondent-specific characteristics (Bonsall and Lythgoe, 2009).

read the information provided or to carry out the choice tasks and the incidence of inconsistent choices (Vista *et al.,* 2009). We also investigated whether the incidence of inconsistent choices varies across the sequence of choices carried out by a respondent, to test whether respondents' preferences evolve throughout the experiment and whether such a 'learning effect' has any impact on choice consistency.

In the last part of the questionnaire, we gathered respondents' socio-economic data and other information about their current consumption of organic food. The sample comprised of 201 respondents, and the survey was administered between December 2012 and February 2013 by a specialized market research company.

The attributes and levels used in the CE are summarized in Table 1. Four attributes are expressed in qualitative terms, while the remaining two are quantitative. The set of attributes and levels described in Table 1 constitutes a full factorial design with 3^5 x 6 = 1,458 combinations. By means of a fractional factorial design, which allows the estimation of the main effects, the total number of combinations was reduced to 36, which were blocked into six groups of six cards. The best fraction of the design was determined by minimizing D-error from a set of candidate designs using Bayesian techniques in NGENE V.1. (for a general overview of efficient experimental design literature see Rose *et al.* (2011) and references cited therein).

Table 1: Attributes and levels of the choice experiment

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3. Methodology

The frequency of choice inconsistencies in the sample is first analysed descriptively. In a second step we investigate possible factors driving inconsistent choices by means of a logistic regression of the incidence of inconsistencies as a function of demographic variables and the time required for reading the information and executing the CE. In the regression, we use the 10^{th} and 90^{th} percentiles as thresholds for extremely fast and slow reading and completion of the CE. The 10th percentile was used, because it approximately matched with the minimum time needed to read the information measured in the pre-test of the survey and in the focus groups (380 seconds). The 90th percentile was chosen to identify respondents, who took a very long time for responding[7].

Inconsistent choices may also originate from choice task difficulty, especially in the first choice tasks, in which respondents may still become more familiar with how to respond to the choice questions (Carlsson *et al.*, 2012). We test for this effect by comparing the frequency of inconsistent choices across choice occasions using standard t-tests.

The model chosen for the analysis of the choice data is the Generalized Multinomial Logit Model (GMNL) and data analysis was carried out with NLOGIT 5 software. The GMNL model allows taking respondents' taste heterogeneity into account, and permits us to test if the treatment of choice inconsistencies affects the variance of the error. The GMNL model nests the scale heterogeneity multinomial logit model and the mixed logit model, and is particular suitable to shed light on whether the heterogeneity in the choice data is better described by taste heterogeneity, scale heterogeneity or a mixture of the two (Fiebig *et al.*, 2010). In this model the utility of respondent *n* from choosing alternative *j* in choice situation *t* is given by:

$$U_{njt} = [\sigma_n \beta + \gamma \eta_n + (1-\gamma)\sigma_n \eta_n] x_{njt} + \varepsilon_{njt} \quad [1]$$

where σ_n is the scale parameter of person *n*, β is the vector of mean attribute utility weights, η_n is the vector of individual-specific deviations from the mean attribute utility weights, γ is a parameter bounded between 0 and 1, which controls how the variance of residual taste heterogeneity varies with scale in a model that includes both[8], x_{njt} is the vector of attribute values of alternative *j* and ε_{njt} is the

[7] In analyses not shown here, we employed different thresholds (5th/95th and 20th/80th percentiles), but results did not differ from the ones described in this study.

[8] Fiebig *et al.* (2010) identified two ways of specifying the GMNL model. GMNL model type I, where the individual-specific standard deviation of the attribute utility weights (η_n) is independent of the scaling of β; and GMNL model type II, where the η_n is proportional to the scale parameter of an individual (σ_n). The γ parameter reveals whether in a particular dataset the heterogeneity structure is closer to the type I or the type II GMNL model. As $\gamma \rightarrow 1$, the model approaches to GMNL type I, whilst as $\gamma \rightarrow 0$ it approaches to type II.

error term assumed to be identically and independently distributed following an extreme value distribution.

Given that σ_n and β enter in the estimation as a product, a normalization either in σ_n or in β is necessary to identify the parameters. Conventionally, the mean of σ_n is set to 1 so that β describes the mean utility of the attributes. Furthermore, being a scale parameter, σ_n must be positive. To achieve both goals Fiebig *et al.* (2010) proposed the following transformation:

$$\sigma_n = \exp(\sigma + \tau\varepsilon_0) \qquad [2]$$

where $\hat{o}$ is a parameter to be estimated, σ *is* = $-\tau^2/2$ and ε_0 is ~N(0,1). Equation [2] allows quantifying the individual heterogeneity in the scale parameter, but does not help to explain individual differences in scale. Individuals may be 'consistently inconsistent' in their choices, for example if their choices are driven largely by pro-environmental social norms. This would result in lower error variances. However, respondents with preferences that are not well-formed or that expend little effort in responding to the choice questions may have greater variances of the error term. To test whether the incidence of inconsistent choices results in lower or greater error variance, we specify the scale parameter as a function of whether an individual chose inconsistently:

$$\sigma_n = \exp(\sigma + \tau\varepsilon_0 + \delta I) \qquad [3]$$

where I is a dummy variable that equals one if an individual has chosen inconsistently, and δ is a parameter to be estimated. The analyses of scale heterogeneity as a function of inconsistent choice occurrence have been carried out using scaled multinomial logit models, given that the GMNL models did not converge when heteroskedasticity is allowed[9].

[9] The scaled multinomial logit model is a particular form of the GMNL model which assumes constant preference parameters across individuals. As such, choice heterogeneity is modelled by focusing on the scale heterogeneity, considering that for some individuals (those with inconsistent choices in our case) the scale of the idiosyncratic error term is different from that of other individuals.

The parameters are estimated using a simulated log likelihood procedure with 250 Halton draws. The simulated choice probabilities of respondent *n* to choose alternative *j* in choice situation *t* are calculated as:

$$P(j|x_{nt}) = \frac{1}{D}\sum_{d=1}^{D}\frac{\exp(\sigma^d\beta+\gamma\eta^d+(1-\gamma)\sigma^d\eta^d)x_{njt}}{\sum_{k=1}^{J}\exp(\sigma^d\beta+\gamma\eta^d+(1-\gamma)\sigma^d\eta^d)x_{njt}} \quad [4]$$

where *d* stands for the simulation draws taken from a multivariate normal distribution with mean 0 and variance-covariance matrix Σ for the η parameters and from a standard normal for ε.

As in all random parameter models, the random distribution of the coefficients must be exogenously specified by the analyst. After testing several alternatives, the final model specification assumed individual tastes to follow a normal distribution for the environmental and employment attributes, and a constrained triangular distribution for the *tax* attribute. The reason for choosing a constrained triangular distribution for *tax* was to avoid very long tails in the distribution of the cost parameter, while still allowing for heterogeneity in sensitivity to cost. Other model specifications, such as the mixed logit model, the latent class model and the covariance heterogeneity model have also been tested during the model selection. These models have been dismissed, because they were found to be statistically inferior relative to the GMNL[10].

We also added interactions of socio-economic characteristics and attitudinal variables with the alternative-specific constant for the *status quo* alternative and with *tax* to the specification of the indirect utility function. These interactions allowed describing observed variability in choices that is not captured via the random taste parameters. In particular, we included interactions between the constant and both respondents' income (K*INC) and their consumption habits regarding organic products (K*CONS). Additionally, we added interactions between the respondents' main reason for consuming organic products and the *tax* attribute[11].

[10] An example of the results using a mixed logit model can be found in Rocamora *et al*. 2014.

[11] Because we are interested in WTP for different policy outcomes resulting from an expansion of organic farming, we have to consider respondents as taxpayers, regardless of whether they consume organic products or

Six models were estimated to investigate the impact of choice inconsistencies on WTP. The benchmark model (model 1) assumes that there are no inconsistencies in respondents' choices, as typically done in a CE study. In a second model, we use the choice data collected after giving respondents the opportunity (but not prompting them) to revise inconsistent choices detected via their stated maximum WTP for the 'best' possible outcome in terms of environmental and social conditions (model 2). The next models (models 3, 4 and 5) form a group in which the choices that remain inconsistent after the revision made by respondents are either accepted by the analyst or removed from the consideration set. The three models differ in the threshold of exceeding stated WTP that is used to accept a choice and thus consider it to be consistent. In model 3 we assume that a choice is still inconsistent if, after the revision made by the respondents, the cost of the chosen alternative is more than 130 % higher than the stated maximum WTP[12]. Models 4 and 5 allow violations of the maximum WTP between 30 % - 130 % and between 0 % - 30 %, respectively. The cutoff values have been chosen to divide the inconsistent choices evenly (33rd and 66th percentiles) into three categories of violation according to the distribution of the magnitude of violations. As such, at least qualitatively, the resulting categories describe large (>130 %), medium (31 % - 130 %) and small (≤30 %), violations of the stated price cutoff. Due to the removal of inconsistent choices, the number of observations decreases progressively as the assumptions regarding acceptable violations of the stated cutoffs become stricter. In model 6, all inconsistent *individuals* (not just choices) have been omitted from the sample. Finally, to shed light on whether scale differs between individuals depending on whether they have made an inconsistent choice or not, we present the results of a scale multinomial logit model in which we allow heteroskedasticity in the scale parameter as a function of whether an individual chose inconsistently and whether s/he retains the choice after revision. Table 2 summarises the main characteristics of all models.

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not. However, previous research (e.g., Hughner *et al.*, 2007; Roddy *et al.*, 1996; Squires *et al.*, 2001; Soler *et al.*, 2002) indicates that environmental concerns are sometimes a driver for consuming organic products. We therefore expected that respondents who declared to consume organic products for environmental reasons show a larger WTP. Three interactions were used in the model; the first was between the tax attribute and a dummy variable indicating that respondents stated that they consume organic products mainly because they are healthier (T*CONS H); the second between the tax attribute and a dummy for the environment as the main stated reason for consuming organic products (T*CONS E); the third interaction between tax and a dummy capturing better taste as the main reason for consuming organic products (T*CONS OL).

[12] For example, if a respondent declares a maximum WTP of 10 EUR but chooses an alternative with an associated cost of 20 EUR, the violation of the stated maximum WTP is 100 % ((20 €-10 €)/10 €).

Table 2: Description of the estimated models

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Theoretically, this approach makes use of the general notion of Swait's (2001) cutoffs to incorporate non-compensatory decision rules into discrete choice models. Cutoffs represent respondent-specific attribute level thresholds which, if exceeded or 'violated', have implications for choice of the affected alternatives. Cutoffs can be viewed by the analyst as 'hard' or 'soft'. When a 'hard' cutoffs perspective is assumed, no violation of cutoffs is allowed (as in models 5 and 6). However, empirical research has shown that individuals sometimes violate (consistently) their cutoffs (Huber and Klein, 1991; Swait, 2001). Accordingly, there should be a positive probability of choosing alternatives that violate cutoffs without considering these choices as inconsistent. The literature refers to this as 'soft' cutoffs (e.g., Swait, 2001; Bush *et al*., 2009; Castro *et al*., 2013)[13]. To model soft cutoffs, in models 3 and 4 we only consider a choice to be inconsistent if the violation relative to the price is larger than the assumed price cutoff.

4. Results

4.1. Analysis of choice inconsistencies

The characteristics of the sample relative to Andalusian population statistics are reported in Table 3. The sample is representative for Andalusia with respect to gender (chi squared=0.29; p-value=0.99) and the distribution of the population amongst the seven Andalusian provinces (chi squared=0.29; p-value=0.99). However, it is formed by younger (chi squared=64.04; p-value=0.00) and higher educated citizens (chi squared=136.63; p-value=0.00) relative to the general population.

Table 3: Sample features

[13] Swait (2001) and Bush *et al*. (2009) allowed respondents to violate the stated cutoffs by applying a utility penalty to chosen alternatives, which contained unacceptable attribute levels ('soft' cutoffs approach). However, they did not allow respondents to modify the choices that violated the stated cutoffs.

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In the choice experiment, 15 respondents (7.5 % of the sample) were identified as protesters based on responses to follow-up questions. Protesters were omitted, resulting in a final sample of 1,116 observations for model estimation. Choice inconsistencies were revealed by comparing the cost of the chosen alternative in the CE with the maximum WTP stated for the 'best' possible scenario according to the attribute levels. 112 interviewees (56 % of the sample) were detected to be inconsistent in at least one of their choices; in particular, among the respondents who made inconsistent choices, 63 % are found to have made one or two inconsistent choices, 34 % between three and five inconsistent choices, and the remaining 3 % were inconsistent in the whole set of choices. This corresponds to a total of 263 inconsistent choices, or 24 % of the total. Regarding possible factors that drive inconsistent choices, the results of the logistic regression show that the educational level is the only significant explanatory variable in the model (Table 4). In line with Salensminde (2002), highly educated respondents have a lower probability of being inconsistent. Interestingly, the results indicate that neither the time spent on reading the information provided nor on carrying out the choice exercise is related to the incidence of choice inconsistencies.

Table 4: Binary logistic regression for inconsistencies
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The analyses regarding the time spent by respondents on each of the choice occasions are summarised in Table 5. Results show that on average respondents were increasingly faster in completing the choice tasks as they move through the sequence of choice tasks. The decline in completion times is particularly pronounced for the first two tasks. The average time spent is almost halved for the second task relative to the first, and is further reduced by a third when comparing the second and the third choice task. The additional time respondents took in answering the first choice questions is likely due to an initially limited understanding on how to best carry out the trade-offs between attributes and comparisons across alternatives, given that most respondents never experienced this type of survey before, and probably related to identifying choice processing strategies that are optimal to them to be used in the following choices. This result may be attributed to an institutional learning effect (Bonsall and Lythgoe, 2009; Carlsson *et al*., 2012), which reflects how people learn to process the information more rapidly as they become more experienced. Previous studies in the literature found similar results, for example Haaijer *et al.* (2000) and Rose and Black (2006).

Along the sequence of choice tasks, the frequency of inconsistent choices varies between 19 % and 25 %, and is slightly elevated for the first three choices. However, the differences are not statistically significant[14]. This finding is an indication that value learning (i.e., 'discovering' preferences for a specific change, see Plott, 1996) or strategic learning (i.e., learning about strategic opportunities that arise from sequential choice, see for example Scheufele and Bennett, 2012) are unlikely to have influenced the incidence of inconsistent choices. Also, it indicates that the design of the questionnaire, and in particular the information provided to respondents prior to the first choice task, was successful in conveying a clear understanding on how to carry out the choice tasks.

Table 5: Analysis of response times and incidence of inconsistent choices
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The number of respondents with inconsistent choices was reduced to 71 (35 % of the sample) after providing them with the opportunity to revise their initial choices, which correspond to 155 inconsistent observations (14 % of the sample). This reveals that, out of the choices that were initially detected to be inconsistent (24 % of all choices), 42% have been corrected through the iterative procedure and 58% remained inconsistent. Different explanations for the correction or the confirmation of inconsistent choices can be offered. Respondents who corrected their inconsistent choices may have realised that in the initial choice task they had deliberately chosen the 'best' alternatives irrespective of cost considerations due to ethical positions, environmental attitudes and social norms, or that they have made errors due to little effort expended on choosing or due to general

[14] We tested whether the proportion of inconsistencies was statistically different along the sequence of choices by means of a chi-squared test, and found that at the 5 % confidence level, the incidence of inconsistencies does not differ across the sequence.

disinterest in the choice task. Another possible reason may be the lack of procedural invariance between the two elicitation methods employed. The maximum WTP stated in the open ended CV question may differ from the maximum WTP arising from choices made based on the comparison of the alternatives in the choice cards. Roe *et al* (1996) and Salensminde (2003) observed that CE, compared to open ended CV, tends to capture respondents' relative valuation rather than their absolute valuation, which is more in line with their budget constraints. As such, it should be expected that the values obtained from open ended CV would be lower than those derived through CE. Irrespective of the underlying reason, once respondents were alerted of the inconsistency in their responses, they made a rational decision to either corrected or retained their initial choices.

One third of the remaining inconsistent choices entail a small violation of the price cutoff (lower than 30 %), one third a medium violation (between 31 % and 130 %) and the remaining a large violation (>130 %). However, not all of these choices are necessarily revealing a behaviour that is inconsistent with (bounded) rational choice of respondents. In line with the soft cutoffs approach (Swait, 2001; Bush *et al*. 2009), there is a positive probability that individuals deliberately violate their price cutoffs (maximum WTP), because the disutility of the violation is lower than the disutility of choosing the second best option. Another possible reason is that respondents' preferences are vague and affected by a degree of uncertainty or fuzziness. In this case, the maximum WTP should not be considered as a fixed amount, but as a distribution with a variance that is proportional to the degree of fuzziness or uncertainty. Carson *et al*. (2012) observed that in this individual choice in a public good context can be expected to diverge significantly from what standard utility theory predicts if preferences are well defined.

4.2. The impact of choice inconsistencies on preferences and WTP

The coefficients of the estimated choice models are displayed in Table 6. The second column reports the results of the initial choices (i.e., ignoring any inconsistencies). All attribute coefficients are highly significant (1 % level) and with the expected sign, except the intermediate level of *soil erosion*, which is significant at the 5 % level. The standard deviation of the random parameters is also significant for all the attributes, revealing a considerable amount of unobserved preference heterogeneity. However, except for the *risk of pollution of water resources*, preference heterogeneity is only present for the attributes' highest levels of improvement. The significance and negative sign of the constant implies preferences towards the *status quo* alternative for reasons not explained by the attributes. The positive sign of the interaction of the constant with a dummy indicating consumption of organic products reveals that consumers have a higher probability of choosing policy-on alternatives relative to those who declared not to consume organic products. The three interactions between dummy variables for stated main reasons for consuming organic products and the *tax* attribute are highly significant. This suggests that there are differences between the marginal disutility of income of those taxpayers who are also consumers of organic products and the rest of the sample; also, within the group 'consumers of organic products', there are significant differences in WTP depending on the main reason stated for the consumption of organic products. In particular, all else equal, individuals who declared to consume organic products mainly for environmental concerns are willing to pay more, an expected result given that the main issue investigated was the environmental care through organic policies in olive orchards. The estimate of the τ parameter is positive and significantly different from zero, indicating the scale parameter differs between individuals across the sample. In particular, the mean and standard error of the estimated parameter reveal that a respondent at the 90^{th} percentile of the scale parameter distribution would have his or her vector of utility weights scaled up by 15 %, whereas a person at the 10^{th} percentile would have his or her vector of utility weights scaled down by 10 %[15]. The estimate of the gamma parameter is not different from zero. This implies, according to the results of Fiebig *et al.* (2010), that the model approaches the G-MNL-II form; i.e., that the variance of the residual taste heterogeneity increases with scale.

The third column of Table 6 describes the model results including the revised choices of respondents. Again, all coefficients are significant at the 1 % level, except for the intermediate level of the *soil erosion*. The model is statistically superior to model 1, gaining 39 units in the log likelihood function at convergence. Unexpectedly, the coefficient associated with a medium

[15] These percentages have been calculated by applying equation 2.

improvement in *biodiversity* is larger than the one associated with a large improvement. Despite the fact that the difference is not statistically significant, it may reveal that respondents find it difficult to discern the differences between the medium and high level of this attribute. The magnitude of the *tax* coefficient is smaller, indicating that the revision of detected inconsistencies reduces the marginal utility of income of those respondents not consuming organic products. The coefficient of the interaction of the constant with respondents' income becomes significant in this model, indicating that after removing inconsistencies, respondents' income affects the probability of choosing the policy alternatives. Interviewees with lower incomes are more likely to choose the *status quo* option. Some of those respondents initially chose an alternative that exceeded their budget constraint, despite the emphasis that the questionnaire placed on taking disposable income and alternative ways to allocate the money into account. This could evidence that budget restriction reminders may fail to be effective for at least some of the respondents. It may also reveal the presence of hypothetical bias, or simply indicate a lack of interest that some members of the on-line panel have in the issue investigated in the survey. The interactions with the *tax* attribute are significant at the 1 % level and show large differences between organic consumers and the rest of the sample, and among organic consumers. Again, and all else equal, the lowest disutility from paying the tax is associated with those who consume organic products for the environmental benefits they create. In this model, the scale parameter is also highly significant and of similar magnitude to the one identified in model 1. This result reveals that overall the correction of choice inconsistencies does not affect the randomness of the choice (variance of the error term). Columns four to six in Table 6 describe the models where inconsistent choices are removed according to increasing violations of the price cutoffs. The coefficients of the models are very similar to the ones in model 2. Again, all coefficients are significant except for *soil erosion*. The *tax* coefficients are progressively smaller in magnitude compared to model 2 as we move towards tighter conditions on consistency, indicating that considering only consistent choices results in a greater disutility among respondents. The interaction of the constant with the income level increases to a 1 % significance level in all models revealing that the probability of choosing the 'policy-on' alternatives is even more strongly related to an individual's income. The interactions between the *tax* attribute and the reasons of consuming organic products remain highly significant and show larger differences in the sensitivity of organic consumers to an increase in tax. The τ parameter in models 3 and 4 is slightly lower than in the other models; however the difference is not statistically significant. Model coefficients containing only consistent individuals are displayed in column seven of Table 6. Attribute coefficients are similar to the previous models and a further decreasing of marginal utility of income is observed. The interaction between the constant and income is no longer significant, revealing that the choices of the fully consistent individuals between 'policy-on' alternatives or the *status quo* are not dependent on the level of income. Interestingly, in this model the τ coefficient is no longer significantly different than zero, revealing that the GMNL model reduces to the simpler mixed logit model. This indicates that heterogeneity in the choices of the consistent individuals is fully described through the systematic component of utility. Overall, consideration, correction or elimination of inconsistencies statistically improves the fitting of the models. From model 1 to model 6, the pseudo R squared statistic increases from 0.22 to 0.35.

Results of the scale multinomial logit model are displayed in the rightmost column of Table 6. The statistical performance of this model is greatly inferior to the GMNL models, indicating that the majority of heterogeneity is explained by the variation in the systematic component of utility and demonstrating that neglecting taste heterogeneity reduces the capacity of the model to describe the respondents' choices. Interestingly, the negative and highly significant value of the delta parameter shows that inconsistent individuals are associated with lower estimates of the scale parameter, i.e. have larger error variances, than consistent ones. This is a signal that inconsistent individuals have preferences which are not as well-formed as those of consistent individuals.

Table 6: Model results
ABOUT HERE

Implicit prices obtained from the GMNL models are reported in Table 7. They demonstrate a positive WTP towards the outlined improvements in all the attributes, except for the intermediate level of *soil erosion* in all models but the first and for both levels of the same attribute in models 5 and

6. As expected, the estimates of implicit prices are lower for all attributes once inconsistent choices are revised or omitted from the data. This decrease in implicit prices may be as large as 66 %, as for the highest level of the *tackling climate change* attribute and the comparison of model 1 and model 6. Except for *biodiversity*, we also observe a decrease in the WTP difference between moderate and high levels of the environmental impacts when moving from model 1 to model 6. In other words, the effect of diminishing marginal WTP becomes more pronounced once inconsistent choices are accounted for.

Table 7: Implicit prices

ABOUT HERE

To test whether there are statistical significant differences between implicit price estimates across the six models, we conducted the Poe *et al.* (2005) test. In Table 8, for sake of space, we show results of the comparison between implicit prices of models 1, 2, 4 and 6, given that the results from models 3 and 5 mirror the ones of models 2 and 5. Results indicate that accounting for inconsistent choices has a significant impact on the implicit prices obtained from CEs. Implicit price estimates of model 1 are significantly lower at the 5 % level compared to all other models, with the exception of the lowest level of some attributes in the comparison with model 2. The significance of the differences increases if we compare estimates of model 1 to the models where inconsistencies have been removed. The additional treatment of inconsistent choices following respondents' own revision does not have a major effect on distributions of marginal WTP, as indicated by the absence of significant differences between implicit prices estimated from model 2 and model 4, and model 2 and model 6. The main result is that, once respondents are allowed to reconsider and eventually correct their inconsistent choices, the resulting welfare measures are no longer different relative to a model estimated from fully consistent individuals.

Table 8: Comparison of implicit prices using a Poe *et al*. (2005) test

ABOUT HERE

As a convergence validity test, the average WTP resulting from the 'best' scenario can be compared with the compensating surplus (CS) estimated using the results of the three CE models by applying the conventional formula of Hanemann (1984):

$$CS = -\frac{1}{\alpha}\left[ln \sum_n \exp V_n^1 - ln \sum_n \exp V_n^0\right] \quad [5]$$

where *CS* is the compensating surplus welfare measure, α is the marginal utility of income and V_n^0 and V_n^1 represent the n*th* individuals' indirect utility functions before and after the change under consideration. The comparison is shown in Table 9.

Table 9: Compensating surplus comparison

ABOUT HERE

The average WTP resulting from the respondents' valuation of the 'best' possible scenario was 27.34 € (standard deviation=17.91). 4.5 % of the sample expressed a WTP greater than 60 €/year and 2.5 % stated a WTP of zero. We assumed a value of 65 €[16] for the 4.5 % of the sample who expressed a WTP greater than 60 €/year, and 0 €/year for the 2.5 % of respondents who declared a genuine zero WTP. In the CE, estimated compensating surplus for the change from the *status quo* to the assumed scenario of maximum improvements in all attributes decreases progressively as we impose stricter conditions for considering a choice as consistent. CS estimates based on model 1 are significantly greater than mean maximum WTP derived from the stated WTP question. In the case of all others models, we find no significant differences between CS estimates. This reveals that once we removed inconsistent choices, the elicitation procedure employed does not impact significantly on the estimated change in welfare. This suggests that differences in the welfare estimates between open ended CV and CE are likely to be caused by the presence of choice inconsistencies in the CE instead of different valuations generated by the two elicitation methods.

[16] To test the sensitivity of the results to this assumption, we also used alternative values of 80 € and 100 €. Results did not differ significantly from the reported one.

5. Discussion

This study investigated the impact of choice inconsistencies in CEs using data from an on-line survey on preferences towards the environmental and social impacts of organic olive farming in mountainous areas of Andalusia, South of Spain. The sample of Andalusian citizens was younger and more educated relative to the general population, and therefore results have to be treated with caution if the reader wishes to use WTP estimates for policy purposes. The difficulty in approaching older and lower educated people also reveals that the internet is still not equally accessible to all parts of the general population in the studied region.

More than half of the respondents made at least one inconsistent choice, in that they selected an alternative whose associated cost was greater than the maximum WTP stated for the 'best' possible alternative. The large proportion of choice inconsistencies found in this study is particularly worrying given that the sample comprises respondents, who on average are more educated relative to the general population, and because efforts have been made in reminding respondents about the individual budget restrictions as well as the existence of other substitute goods and services respondents may prefer to buy. Indeed, respondents with higher education were less likely to choose alternatives that violate their self-stated maximum WTP and needed less time to read the information package and to complete the choice tasks. Therefore, differences in response times and incidence of inconsistent choices in our study appear to be related to the cognitive capability of respondents indicated by their level of educational attainment. This casts doubts on the capability of the general population to process the information provided in a way that results in consistent choices, and as a consequence questions the policy relevance of the results..

The large percentage of inconsistent choice is particularly worrying also because there is no corroborative evidence that this result comes from respondents disengaged with the issue investigated and the choice task. Using time to read and complete the choice tasks as a proxy for survey engagement, we find that only a small proportion of respondents appeared to have taken either very little time, or were disproportionally slow to complete the survey. Additionally, the fact that respondents took longer to respond to the first and second choice task compared to subsequent ones reveals that they took the choice task seriously. Because the frequencies of choice inconsistencies do not vary along the sequence of choice tasks, we are confident in attributing these longer response times for the initial tasks to an institutional learning effect.

Overall, the results of this study question, whether reminding respondents of budgetary restrictions and substitutes to the good and services evaluated is effective to improve the quality of the estimates obtained in CEs. According to our results, the simple budget and substitute reminders are not sufficient to avoid that respondents choose alternatives in the CE with a cost exceeding their stated maximum WTP. This result is in line with previous research on attribute processing strategies, which found that non-attendance to the cost attribute can be very large (Campbell *et al.,* 2008; Scarpa *et al.,* 2009). As pointed out by Scarpa *et al.* (2009), more research is required to identify supplementary questions that provide the analyst with an opportunity to test choice processes and outcomes based on information that is individual-specific. The iterative procedure proposed in this study contributes to this line of research. The use of 'cheap talk scripts'[17] may be another approach worth investigating. In this context, Tonsor and Shupp (2011) found that the use of cheap talk scripts can influence WTP estimates derived from on-line surveys and produce more reliable WTP estimates.

Choice inconsistencies may be due to several causes, each deserving further investigation. First, respondents may be reluctant to choose the 'policy-off' or *status quo* alternative if the proposed policies concern sensitive topics as is often the case in environmental valuation. Within this context, contributions from social psychology in CV surveys reveal that psychological factors can be superior to standard socio-economic variables in understanding the motives behind the choices (Spash *et al.*, 2009). Choice inconsistencies may also arise because the information gathered through on-line surveys and in repeated choice situations in relation to public goods and policies is not fully incentive-compatible given that it lacks a plausible mechanism for consequentiality. More research is required

[17] Cheap talk scripts inform respondents that in similar studies using stated preference methods, people have a tendency to overestimate how much they are willing to pay compared to their actual (true) willingness to pay. Cheap talk scripts were initially implemented by Cummings and Taylor (1999) in an attempt to reduce hypothetical bias in CV.

to determine the exact impact of this effect in environmental contexts. Alternatively, respondents may deliberately violate their self-reported cutoffs in certain circumstances in line with the 'soft' cutoffs approach described by Swait (2001). For example, a respondent may retain the most expensive alternative as his/her preferred choice despite violating his/her price cutoff, because the second best alternative is offering clearly inferior overall trade-offs between costs and benefits. This may also occur when respondents' preferences towards the price cutoffs are vague or uncertain (Carlsson *et al*., 2012). In this case, their true maximum WTP lies in an interval of values which respondents are definitely willing to pay and definitely not willing to pay and cannot be summarised by a fixed amount as shown on choice cards. In this context, Olsen *et al*. (2011) observed that the utility difference has a clear impact on the probability of respondents reporting *ex post* that they are certain or very certain of their choice. The larger the utility difference between the alternative chosen and the best of the remaining alternatives, the more likely it is that respondents are confident about their choice. The incidence of choice inconsistencies may also be related to the elicitation format used. The comparison of two or three alternatives in the CE may lead to a relative valuation of the good by respondents, which clearly depends on the subset of alternatives evaluated in each of the choice cards and may differ from an absolute value expressed in an open ended CV question. Finally, having to go through an iterative procedure that implies repeatedly answering to choice tasks may give rise to decision fatigue; not revising their initially inconsistent choice is then a strategy that demands little cognitive effort.

The approach to identifying inconsistent choices and considering them in the choice model simultaneously tackles several important problems related to treating inconsistent choices in CE data. First, it avoids that inconsistent observations are being ignored, which would bias results. Second, it enables the revision of the initially inconsistent choices and therefore avoids a considerable loss of information had these choices been omitted. Third, it allows the analyst to identify the factors that explain choice inconsistencies giving the possibility, at the study design stage, to reduce the impact of these inconsistencies on results. For instance, if the analyst is interested in gathering information that is representative of the general population and uses only consistent responses at the same time, s/he should oversample those part of the population which are more likely to be inconsistent (less educated people in this case study). Fourth, it does not require the analyst to make assumptions about which of the choices are actually considered as inconsistent (Bush *et al.*, 2009). Finally, it does not require knowledge on the causes of inconsistency, which may be very diverse and heterogeneous across the sample.

Focusing on the CE model results, the revision of inconsistent choices and an additional subsequent omission of the residual inconsistencies significantly affect WTP measures. On average across all attributes, WTP is higher by 78 % if inconsistencies are ignored (model 1) relative to WTP estimates derived from the model that is based on revised choices (model 2). The upward bias of WTP estimates based on model 1 increases further as assumptions on whether a choice is being considered as consistent become stricter. For example, if the analyst accepts a 30 % deviation between the maximum stated WTP and the cost of the chosen alternative in the CE, the bias increases to 133 % (model 4). If all remaining inconsistent choices or individuals are omitted, the marginal WTP is 146 % (model 5) and 199 % (model 6) of the average values based on model 1. These results clearly point to the importance of identifying and testing the impact of inconsistent choices in CEs.

For policy purposes, the dual character of citizens, who can act as consumers and/or taxpayers, should be also taken into account when determining WTP. Although the sample is not representative of the Andalusian population, it is ‘representative’ of consumers of organic products, which on average are more educated and younger than the general population (Briz and Ward, 2009). Results indicate that consumers of organic products have larger WTP for an environmental program that results in an expansion of organic farming. Amongst consumers of organic products, the largest increase in WTP is observed for those respondents, who state to consume organic products mainly for environmental reasons, followed by lower increases in WTP for respondents stating health and organoleptic reasons as main drivers of choosing organic products.

Several limitations apply to this study. First, choice task complexity (as defined by observable dimensions of choice tasks such as number of alternatives, attributes and attribute levels) was not varied. Choice task complexity has been observed to impact both on the systematic and the random component of utility (Dellaert *et al.*, 2012), and may have a significant effect on the incidence of choice inconsistencies. Second, choice inconsistencies may be related to any attribute used in the choice set, whilst in this study we only focus on the cost attribute. Third, we obtained information on the maximum WTP for the 'best' scenario by means of a direct question and used it for detecting the choice inconsistencies after the completion of the CE. The tax values shown on preceding choice cards may have influenced the stated maximum WTP by respondents and the elicitation format employed may have impacted the stated WTP. In addition, we implicitly assumed that this value represents the true maximum WTP without having given respondents the opportunity to reconsider it and without measuring the respondents' certainty in the response.

The use of information on revised choices made by respondents may introduce endogeneity bias in the coefficients of the models estimated with the revised responses. The respondents' valuation of maximum WTP may change over time as consumers accumulate information about their choice tasks or when the decision environment changes (Swait, 2001). Therefore, the assumption of exogeneity of information on self-reported cutoffs may not always be warranted[18]. However, model 5 and model 6 are not affected by this potential bias, given that they are estimated from a reduced sample where no information about the respondents' maximum WTP is included in the model. The lack of significant differences between the welfare estimates of the models where we included information on self-reported cutoffs (model 2, 3, and 4) and models 5 and 6 reveals that, if endogeneity bias exists in this dataset, its impact is not significant. The determination of the exact magnitude of this bias on welfare estimates depending on different ways of using respondent self-reported information remains an interesting area of future research.

[18] A common approach to overcoming the problem of endogeneity is to use instrumental variables in model estimation. However, it may be very challenging to find suitable instrumental variables for self-reported price cutoffs. An example of this approach is Ding *et al*. (2012).

6. Conclusions

We report findings from a study using an on-line format to determine the impact of inconsistent choices on welfare estimates derived from CEs. More than half of the sample carried out at least one inconsistent choice that is at odds with the self-reported maximum WTP for the 'best' possible outcome. These inconsistencies were not found to be related to the respondents' response times needed for processing and completing the survey, which was used as a proxy for respondents engagement with the issue investigated. Importantly, when faced with the responses identified to be inconsistent, a considerable proportion of the sample chose to retain their initial choice. The results provide clear evidence on the necessity to consider appropriate supplementary information in on-line CEs that can be used to identify inconsistencies at an individual level, in order to increase realism and accuracy of the conclusions deduced from CEs used for environmental valuation.

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Tables

Table 1: Attributes and levels of the choice experiment

Attribute	**Levels**	**Label**
Tackling climate change	**Low**	CC1
	Medium	CC2
	High	CC3
Biodiversity	**Low**	BD1
	Medium	BD2
	High	BD3
Risk of pollution of water resources	**High**	WP1
	Moderate	WP2
	Low	WP3
Soil erosion	**High**	SE1
	Moderate	SE2
	Low	SE3
Agricultural employment	**0 %**, 5 %, 10 % increase	AE
Tax	**0**, 2, 7, 14, 23, 35, 51 €/year	T

Note: Levels of the current situation are shown in bold; the labels indicate the codes used in the model.

Table 2: Description of the estimated models

Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**
	GMNL						**SMNL**
Treatment	**No treatment**	**Corrected as stated**	**Inconsistent choices are removed if the violation relative to the stated maximum WTP is larger than X % of the maximum stated WTP**			**All inconsistent individuals removed**	**Allows heteroskedasticity in the scale parameter as a function of inconsistent individuals**
			X>130 %	X>30 %	X>0 %		
Observations	1116	1116	1067	1004	961	690	1116

Table 3: Sample statistics

Variables	Values	Sample data (%)	Population data (%)
Gender	1= Female	48.3	50.9
Educational level	1=None or primary studies	8.5	23,6
	2= Secondary studies	30.3	50.9
	3= High degree studies	61.2	25.5
Age	1= 18-34 years old	51.2	31.0
	2= 35-65 years old	48.8	51.5
	3= More than 65 years old	0.0	17.5
Consumer of organic products (CONS)	1= consumer of organic products	69.2	43.2
Reasons for consuming organic, % of consumers.	health (CONS H)	36.0	
	environment (CONS E)	32.4	
	organoleptic (CONS OL)	21.6	
	Other reasons	10.1	
Income in €/month (INC)	Lower than 600	7.5	40.5
	Between 600 and 1,000	16.4	39.2
	Higher than 1,000	76.1	20.3

Table 4: Binary logistic regression for inconsistencies

Variables	**Coefficients**	**St. errors**	**P-values**
Constant	0.619	0.652	0.342
Education	-0.668	0.311	0.032
Gender	0.048	0.305	0.876
Age	-0.009	0.016	0.575
Consumers of organic products	0.444	0.332	0.181
Time CE 10th percentile	-0.102	0.497	0.838
Time CE 90th percentile	0.004	0.490	0.994
Time Reading 10th percentile	-0.033	0.499	0.948
Time Reading 90th percentile	0.250	0.500	0.616

Table 5: Analysis of response times and incidence of inconsistent choices

	Average response time (seconds)	Standard deviation	Inconsistent Choices (%)	T-test[a]
Choice Task 1	70.02	32.47	23.4	
Choice Task 2	39.16	25.04	24.9	T_{1-2}=10.24
Choice Task 3	26.93	16.25	23.9	T_{2-3}=5.63
Choice Task 4	23.41	13.06	19.4	T_{3-4}= 2.37
Choice Task 5	23.34	15.73	19.9	T_{4-5}= 0.06
Choice Task 6	20.67	10.12	19.4	T_{5-6}= 2.10

[a] Between time choice task n-1, and time choice task n

Table 6: Model results

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Attribute	**Betas**	**St. error**	**Betas**	**St. error**	**Betas**	**St. error**	**Betas**	**St. error**	**Betas**	**St. error**	**Betas**	**St. error**	**Betas**	**St. error**
Random parameters in utility functions														
CC 2	0,961***	0,197	0,905***	0,219	0,989***	0,253	0,859***	0,245	1,064***	0,344	1,066***	0,340	1.272***	0.439
CC 3	1,254***	0,294	1,000***	0,267	0,925***	0,286	0,825***	0,285	1,103***	0,391	1,301***	0,456	1.313***	0.435
BD 2	1,208***	0,230	1,375***	0,266	1,349***	0,302	1,274***	0,279	1,509***	0,368	1,362***	0,397	1.405***	0.532
BD 3	1,367***	0,255	1,263***	0,277	1,283***	0,279	1,023***	0,269	1,181***	0,359	1,303***	0,338	1.863***	0.611
WP 2	1,040***	0,224	1,318***	0,273	1,335***	0,286	1,255***	0,256	1,538***	0,411	1,408***	0,386	1.431***	0.523
WP 3	1,632***	0,254	1,928***	0,352	2,015***	0,372	1,823***	0,319	2,008***	0,474	1,862***	0,461	2.309***	0.768
SE 2	0,506**	0,209	0,255	0,214	0,169	0,258	0,016	0,238	-0,281	0,303	0,260	0,333	0.951**	0.420
SE 3	0,916***	0,223	0,630***	0,209	0,569**	0,240	0,456**	0,214	0,366	0,278	0,509	0,336	1.464***	0.546
AE	0,251***	0,040	0,224***	0,040	0,233***	0,043	0,227***	0,044	0,269***	0,063	0,269***	0,058	0.251***	0.087
T	-0,150***	0,021	-0,249***	0,035	-0,260***	0,038	-0,292***	0,044	-0,329***	0,068	-0,354***	0,065	-0.065***	0.023
Nonrandom parameters in utility functions														
Constant *(K)*	-2,108***	0,443	-1,940***	0,411	-2,152***	0,466	-1,927***	0,423	-2,079***	0,492	-2,244***	0,657	-2.251***	0.853
*K*CONS*	0,541**	0,272	0,450*	0,269	0,584*	0,299	0,548*	0,288	0,703**	0,318	0,576	0,397		
*K*INC*	0,093	0,091	0,188**	0,073	0,221***	0,082	0,228***	0,077	0,230***	0,085	0,182*	0,108		
*T*CONS H*	0,063***	0,014	0,105***	0,023	0,097***	0,027	0,102***	0,030	0,077**	0,032	0,098**	0,046		
*T*CONS E*	0,087***	0,016	0,130***	0,025	0,150***	0,029	0,158***	0,032	0,146***	0,034	0,196***	0,049		
*T*CONS OL*	0,049***	0,014	0,073***	0,023	0,079***	0,025	0,088***	0,032	0,084**	0,034	0,042	0,049		
Standard deviations of random parameters														
CC 2	0,188	0,591	0,590	0,445	0,758	0,534	0,663	0,604	0,908	0,575	0,935	0,576		
CC 3	1,390***	0,309	1,365***	0,385	1,443***	0,410	1,702***	0,459	1,858***	0,586	1,225***	0,466		
BD 2	0,517	0,519	0,434	0,541	0,916*	0,539	0,645	0,591	0,378	0,834	0,233	1,050		
BD 3	0,870**	0,349	1,272***	0,385	1,230***	0,404	1,030**	0,412	1,499***	0,494	1,058*	0,606		
WP 2	0,847***	0,325	0,401	0,406	0,665	0,453	0,560	0,355	0,881**	0,416	0,798*	0,470		
WP 3	1,248***	0,319	1,419***	0,351	1,556***	0,395	1,084**	0,454	1,457***	0,526	1,639***	0,521		
SE 2	0,348	0,488	0,624	0,394	1,127***	0,374	0,924**	0,435	1,047*	0,542	0,802	0,548		
SE 3	0,870***	0,337	0,569	0,395	0,908**	0,433	0,238	0,685	0,867	0,590	1,082*	0,596		
AE	0,165***	0,041	0,213***	0,042	0,205***	0,044	0,200***	0,047	0,190***	0,056	0,234***	0,054		
T	0,150***	0,021	0,249***	0,035	0,260***	0,038	0,292***	0,044	0,329***	0,068	0,354***	0,065		
Variance parameter tau in GMX scale parameter														
Tau scale	0,422***	0,114	0,413***	0,149	0,348**	0,143	0,352**	0,144	0,424**	0,195	0,220	0,223	2.167***	0.323
Heterogeneity in the scale parameter														
													-0.719***	0.189
Weighting parameter gamma in GMX model														
Gamma	0,000	0,372	0,000	0,334	0,000	0,369	0,000	0,397	0,000	0,457	0,000	0,539	*Fixed parameter*	
Model features														
LL	-951,38		-912,48		-860,45		-791,05		-743,71		-507,29			
R^2	0,22		0,26		0,27		0,28		0,30		0,33			
N	1116		1116		1067		1004		961		690		1116	

Table 7: Implicit prices

	Implicit prices Model 1		Implicit prices Model 2		Implicit prices Model 3		Implicit prices Model 4		Implicit prices Model 5		Implicit prices Model 6	
Attribute	**Value**	**Confidence interval**	**Value**	**Confidence interval**	**Value**	**Confidence interval**	**Value**	**Confidence interval**	**Value**	**Confidence interval**	**Value**	**Confidence interval**
CC 2	9.7	(6.08; 15.94)	5.3	(3.25; 8.54)	5.5	(3.18; 9.00)	4.4	(2.21; 7.46)	4.4	(1.96; 7.16)	3.4	(1.86; 7.04)
CC 3	12.4	(8.00;19.27)	5.7	(3.07; 9.53)	5.2	(2.46; 8.95)	4.1	(1.58; 7.29)	4.6	(1.84; 8.12)	4.2	(1.93; 9.01)
BD 2	12.1	(8.29; 19.33)	8.0	(5.73; 12.60)	7.8	(4.98; 13.13)	6.4	(3.93; 10.14)	6.4	(3.65; 10.57)	4.5	(2.39; 9.48)
BD 3	13.8	(9.59; 21.37)	7.3	(4.83; 11.86)	7.3	(4.76; 12.55)	5.1	(2.73; 8.08)	5.0	(2.44; 8.35)	4.3	(2.45; 9.18)
WP 2	10.3	(6.99; 16.20)	7.5	(5.48; 10.93)	7.5	(5.33; 11.93)	6.4	(4.36; 9.46)	6.5	(4.24; 8.98)	4.6	(3.03; 8.47)
WP 3	16.3	(12.23; 24.86)	11.1	(8.67; 16.26)	11.5	(8.85; 17.60)	9.2	(6.88; 13.14)	8.5	(5.95; 11.98)	6.2	(4.67; 11.34)
SE 2	5.2	(1.15; 10.75)	1.5	(-1.00; 4.62)	1.1	(-1.88; 4.95)	0.1	(-2.22; 2.81)	-1.0	(-3.20; 1.62)	0.9	(-1.49; 4.46)
SE 3	9.1	(5.44; 15.54)	3.7	(1.40; 7.23)	3.2	(0.66; 6.92)	2.3	(0.35; 5.18)	1.6	(-0.89; 4.17)	1.6	(-0.73; 5.05)
AE	2.5	(1.92; 3.58)	1.3	(0.99; 1.97)	1.3	(1.01; 1.96)	1.2	(0.82; 1.69)	1.1	(0.78; 1.52)	0.9	(0.68; 1.65)

Table 8: Comparison of implicit prices using a Poe et al. (2005) test

	Model 1 versus			Model 2 versus		Model 4 versus
	Model 2	**Model 4**	**Model 6**	**Model 4**	**Model 6**	**Model 6**
CC 2	**	***	***	NS	NS	NS
CC 3	***	***	***	NS	NS	NS
BD 2	NS	**	***	NS	NS	NS
BD 3	**	***	***	NS	NS	NS
WP 2	NS	**	***	NS	NS	NS
WP 3	**	***	***	NS	NS	NS
SE 2	NS	**	**	NS	NS	NS
SE 3	**	***	***	NS	NS	NS
AE	***	***	***	NS	NS	NS

Table 9: Compensating surplus comparison

	Stated WTP	CE					
		MODEL 1	**MODEL 2**	**MODEL 3**	**MODEL 4**	**MODEL 5**	**MODEL 6**
Compensating Surplus (€) **(confidence interval)**	27.34 (23.40; 31.28)	51.61 (41.08; 62.14)	28.04 (22.24; 33.84)	26.11 (20.28; 31.94)	20.47 (15.34; 25.60)	19.89 (15.04; 24.74)	19.40 (13.62; 25.17)

Figures

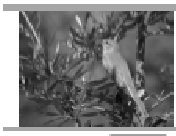
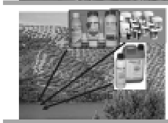
Impact		Current situation	Alternative 1 **with organic farming**	Alternative 2 **with organic farming**
	*Tackling climate change*	**Neither alternative 1, nor alternative 2 compensate the tax increase. I prefer the current situation**	low	**medium (-25 % Co_2)**
	*Biodiversity (density of animals and plants)*		low	**medium (+40 %)**
	*Risk of pollution of water resources*		elevated	**reduced**
	*Soil erosion*		**moderate (-22 %)**	**moderate (-22 %)**
	*Increase in agricultural employment*		**+ 10 %**	**+ 10 %**
	*Increase in your taxes (€/year)*		**14 €**	**23 €**
Which option do you prefer?		☐	☐	☐

Figure 1: Example of a typical choice card

Impact		Current situation	Best situation **with organic farming**
	***Tackling climate change***	low	**high**
	***Biodiversity (density of animals and plants)***	low	**high**
	***Risk of pollution of water resources***	elevated	**reduced**
	***Soil erosion***	elevated	**reduced**
	***Increase in agricultural employment***	+ 0 %	**+ 10 %**

Maximum amount I am **willing to pay anually** to achieve the **best situation**

0 €	5 €	10 €	15 €	20 €	25 €	30 €	35 €	40 €	45 €	50	55	60	More than 60 €

Your maximum willingness to pay is inconsistent with your previous choices

*The maximum willingness to pay you just declared is **at odds with** at least one of your **previous choices**.*

That is: previously, you have chosen at least one alternative with an associated cost higher than the one you have declared now for the best situation. Therefore, we are going to show you again your inconsistent choices and we ask you to reconsider them taking into account your maximum willingness to pay for the best possible situation.

Max WTP is consistent with CE choices. The respondent follows with the next section of the questionnaire

Figure 2: The iterative procedure to detect choice inconsistencies.