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TOWARDS SUSTAINABLE AGRI-FOOD SYSTEMS:
BALANCING BETWEEN MARKETS AND SOCIETY

The effect of attribute non-attendance on choice experiments investigating agri-environmental scheme design

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The effect of attribute non-attendance on choice experiments investigating agri-environmental scheme design

Abstract

The objective of this paper is to improve the understanding of attribute non-attendance (ANA) in a choice experiment (CE) investigating farmers' WTA for participating in agri-environmental schemes in southern Spain. Evidence is found of ANA behaviour for both stated and inferred approaches, with models accounting for ANA clearly outperforming those that do not account for it; however, we produce no conclusive results as to which ANA approach is best. In addition, we investigate sources of observed heterogeneity related to ANA behaviour, our results hinting at a positive relationship between ease of scheme adoption and non-attendance to attributes.

Keywords: **Choice experiments; Stated attribute non-attendance; Inferred attribute non-attendance; Willingness to accept; Agri-environmental schemes**

1 Introduction

One of the main issues regarding the use of choice experiments (CE) relates to the continuity axiom. This axiom is based on standard neoclassical consumer theory, assuming unlimited substitutability among attributes. The implication is that respondents are presumed to consider the full profile of available information, making trade-offs between all the attribute levels of the alternatives and behaving as utility maximisers. As a result, the choice of the preferred alternative should reflect fully compensatory behaviour (Hensher *et al.*, 2005). However, there is empirical evidence that these assumptions are frequently violated via non-compensatory decision schemes such as simplified decision rules and information processing strategies ('heuristics'), resulting in biased welfare estimates (e.g. Hensher *et al.*, 2005, Colombo and Glenk, 2013). An additional factor is the presence of bounded rationality, which refers to individuals adapting their behaviour according to the context, complexity, familiarity and understanding of the valuation exercise (Colombo *et al.*, 2016). Thus, this heuristic process entails ignoring certain attributes, an effect commonly referred to as attribute non-attendance (ANA). If left unaccounted for, the presence of ANA behaviour may bias welfare estimates. For example, if respondents do not pay attention to the monetary attribute, estimates of marginal utility of income are lowered, which results in inflated welfare measures in willingness to pay (WTP) contexts (Colombo and Glenk, 2013). Therefore, accounting for ANA is strongly recommended, in order to prevent related biases.

Not surprisingly, ANA has received much attention from scholars in the last decade. A large body of literature focuses on modelling respondents' preferences including ANA in an attempt to limit potential biases in welfare estimates (see Leong and Hensher, 2012, for a review). However, most of the above studies concern consumers' WTP for changes in the provision of environmental goods and services. There has been limited research on ANA in the context of willingness to accept (WTA), although an increasing number of studies analyse the preferences of ecosystem service (ES) providers towards incentive-based schemes (see Villanueva *et al.*, 2017, for a review). These studies usually estimate the WTA of ES providers for enrolment in incentive-based schemes, with the underlying assumption being that providers' choices about participation depend on the specific scheme characteristics. However, within this literature, studies have barely touched on the issue of discontinuous preferences. To our knowledge, although there are authors who have reported some continuity issues (Kassahun and Jacobsen, 2015, Greiner, 2016), so far only Espinosa-Goded and Barreiro-Hurlé (2010) have systematically accounted for ANA when investigating ES providers'

WTA. These authors use a stated attribute attendance approach, finding the presence of discontinuous preferences and obtaining moderate improvements in the goodness-of-fit for the models that account for ANA compared to uncorrected models. No studies to date, however, have used an inferred attribute attendance approach in this type of WTA context. Therefore, we aim to provide insights into ANA in this context by using both stated and inferred approaches.

We analyse farmers' ANA behaviour, both stated and inferred, in a CE investigating farmers' WTA for participating in AES. For this purpose, we use data from a case study on olive growers' preferences towards AES design in Andalusia (southern Spain) (Villanueva *et al.*, 2015). Stated preference attendance was accounted for by using debriefing questions, while Hess and Hensher's (2010) methodological approach was used for inferred preference attendance. We use mixed logit models to analyse stated and inferred ANA, with a special focus on the comparison between the two approaches and the impact of ANA on the estimation of WTA. In addition, we investigate sources of observed heterogeneity related to ANA behaviour by using a sequence of bivariate probit models for each attribute.

2 Method

2.1. ANA Model Specification

An ANA preference structure can be directly identified on the basis of ANA self-reported statements in the questionnaire (e.g. Hensher *et al.*, 2005) or from observed choice behaviour based on suitable statistical models (e.g. Scarpa *et al.*, 2009, Hess and Hensher, 2010). In the present study, we investigate two methodological approaches: stated attribute non-attendance (SNA) and inferred attribute non-attendance (INA). In both cases, error-component mixed logit models (EC_MXL), which rely on continuous preference mixing, were used.

For SNA, we used follow-up questions at the end of the sequence of choice sets, with respondents answering whether they attended to each attribute or not[1]. We focus the SNA analysis on the parameter means, in contrast to the approach used by Espinosa-Goded and Barreiro-Hurlé (2010), which focuses on the heterogeneity of means. Once ANA is identified, the ANA behaviour is accounted for by restricting the attribute coefficients –instead of the attribute levels– to zero if an attribute was ignored.

For INA, the approach proposed by Hess and Hensher (2010) (HHA) was followed. HHA makes use of the MXL, which is possibly the most widely used econometric approach for CE applications due to its versatility in allowing for parameter variation across respondents, flexible substitution patterns and correlation with unobserved patterns. As in Hess and Hensher (2010), these models were estimated accounting for unobserved individual preference heterogeneity by specifying random parameters following normal distributions for the hypothetical AES attributes. Those for which standard deviations did not significantly differ from 0, implying an absence of heterogeneity, were treated as fixed effect parameters. Also, the experimentally designed AES alternatives were specified to share a zero-mean error component with standard deviation denoted by η (constant fixed effect for the no-enrolment alternative).

[1] The precise question was: "Which attributes influenced your choices during the sequence of choice sets?". Then, the interviewer enumerated the six attributes and the respondent answered if the attribute influenced her/his choices or not.

The econometric specification is as follows. Let $P_n\ (i/\beta_k)$ be the probability of respondent n choosing alternative i conditional on the vector of taste coefficients β_k, where $\beta_k \backsim f(\beta_k /\Omega)$ allowing for random variations. The probability of respondent n choosing the alternative i is given by:

$$P_n\ (i|\Omega) = \int_{\beta_k} P_n\ (i|\beta_k) f(\beta_k|\Omega)\, d\beta_k \qquad [1]$$

where the MXL choice probability is conditional on Ω. With $j_{n,t}$ giving the alternative chosen by respondent n in choice situation t (taste only varies across the respondents) the log-likelihood for the model is given by:

$$LL(\Omega) = \sum_{n=1}^{N} ln\left(\int_{\beta_k}\left(\prod_{t=1}^{\tau_n} P_n(j_{n,t}|\beta_k)\right) f(\beta_k|\Omega)\, d\beta_k\right) \qquad [2]$$

Although in the calibration of the MXL the estimates of Ω work at the level of the sample, the likely values of parameters of the distribution of β_k for respondents are estimated by conditioning on the observed specific choice patterns for each individual. Let Yn define the serial pattern of observed choices for respondent n, and let $L(Yn|B)$ give the probability of observing this pattern of choices with a specific value for the vector β_k. Then, considering that

$$L(Y_n|\beta_k) = \prod_{t=1}^{\tau_n} P_n(j_{n,t}|\beta_k) \qquad [3]$$

the probability of observing the specific value of B for the sequence of choices of respondent n is given by:

$$K = (\beta_k|Y_n) = \frac{L(Y_n|\beta_k) f(\beta_k|\Omega)}{\int_{\beta_k} L(Y_n|\beta_k) f(\beta_k|\Omega) d\beta_k} \qquad [4]$$

from which the moments of the individual conditional distributions of β_k can be estimated.

The core idea behind using HHA to deal with ANA is that the individual taste differences are captured through the density functions using the deviations from the mean. A posterior analysis of the MXL estimations is performed by conditioning on observed choices, so the estimated conditional mean and variance for each respondent (n) and attribute k is given by $\beta_{kn} \sim N(\mu_{kn}, \sigma_{kn}^2)$. From this point, the coefficient of variation (CV) was estimated for each farmer according to the expression $cv_{kn} = \sigma_{kn}/\mu_{kn}$. In this regard, Hess and Hensher (2010) propose using the CV as a noise-to-signal ratio to distinguish attribute attendance. The authors established the CV value of 2 as the threshold marking the point at which the respondents do not pay enough attention to the attribute to be deemed attended to. They acknowledge that this threshold could be considered somewhat arbitrary, but also claim that it is conservative since the respondent attribute specific normal distribution can be considered as overspread from it.

As with SNA, once ANA has been identified through the INA approach, the ANA behaviour is modelled by restricting the attribute coefficients to zero if an attribute was ignored (Hess and Hensher, 2010).

2.2. Concordance and WTA Estimates

The concordance between SNA and INA was analysed at aggregate and individual levels. To do so, the stated and inferred ANA frequencies were compared in the case of the aggregate approach, whereas the specific individual stated patterns of ANA were compared with the inferred ones in order to obtain the individual concordance level. In addition, the concordance level of ANA patterns between the two approaches was checked at the individual level, but in this case by considering the number of attributes ignored at the same time.

Marginal rates of substitution between non-monetary (NM_i) attributes and the monetary (M) attribute were estimated by calculating the ratio of the negative coefficient of the former attributes to the positive coefficient of the latter [$WTA_{NMi} = -(\mu_{\_NMi} / \mu_{\_M})$]. Since we have two utility functions in our case, one for the *attribute attendance* (AA) group and one for the *attribute non-attendance* (ANA) group, the Total Probability Theorem was employed to estimate the unconditional WTA for the population as follows:

$$WTA = -\left[\begin{array}{l}\left(\frac{\mu_{ANA_{NMi}}}{\mu_{ANA_{Mi}}}\right)\times\left(P_{ANA_{NMi}} \times P_{ANA_M}\right) + \left(\frac{\mu_{ANA_{NMi}}}{\mu_{ANA_{Mi}}}\right)\times\left(P_{AA_{NMi}} \times P_{ANA_M}\right) + \\ \left(\frac{\mu_{ANA\_NMi}}{\mu_{AA\_Mi}}\right)\times\left(P_{ANA\_NMi} \times P_{AA\_M}\right) + \left(\frac{\mu_{ANA\_NMi}}{\mu_{AA\_Mi}}\right)\times\left(P_{AA\_NMi} \times P_{AA\_M}\right)\end{array}\right] \quad [5]$$

with P_{ANA} and P_{AA} being the probabilities of non-attendance and attendance to the attributes, and μ_{ANA} and μ_{AA} the mean parameters estimated for the ANA and AA groups of respondents, respectively.

The parametric bootstrapping approach proposed by Krinsky and Robb (1986) was applied to empirically determine the distribution of marginal WTA for the attributes. To test for significant differences among the alternative approaches applied (not accounting for ANA, SNA and INA), the Complete Combinatorial test suggested by Poe *et al.* (2005) was used.

2.3. Uncovering the Sources of Observed Heterogeneity behind ANA Behaviour

To uncover the sources of observed heterogeneity that could be behind ANA behaviour, a sequence of bivariate probit models (BVP) for each attribute were used. The first equation corresponded to SNA and the second to INA. As the stated and inferred outputs are likely to be linked, the BVP model takes into account the potential correlation among the unobserved disturbances of both equations. The correlation is supposed to be positive, indicating a complementary relationship which leads to unbiased and efficient estimates, as opposed to when univariate probit models are used (Rodríguez-Entrena and Arriaza, 2013). The general specification of the multivariate probit model is (Greene, 2007):

$$\begin{aligned} y_{im}^{*} &= B_m^{'} x_{im} + \varepsilon_{im}, \ (m=1,..., \mathrm{M}) \\ y_{im} &= \begin{Bmatrix} 1 \text{ if } y_{im}^{*} > 0 \\ 0 \text{ otherwise} \end{Bmatrix} \end{aligned} \quad [6]$$

where, in our case, m=1,2 denoting the two types of ANA behaviour (stated vs inferred) for each attribute. In Eq. [6] the assumption is that a rational i^{th} farmer has a latent variable, y_{im}^{*} , which captures the unobserved preferences associated with the m^{th} choice of ANA (stated and inferred). This latent variable is assumed to be a linear combination of farmer and farm observed characteristics that affect the adoption of an ANA behaviour for each AES attribute, x_{im} , as well as unobserved characteristics captured by the stochastic error term ε_{im}. The parameter vector to be estimated is denoted by $B_m^{'}$. The exact measurement of response strengths y_{im}^{*} is latent in nature and its information about the non-attendance of a particular attribute is given by an observed dichotomous vector y_{im} (see Eq. [6]).

A simulated maximum likelihood approach (SML) is used to estimate the BVP, where the probabilities that enter the log-likelihood, its derivatives, and so on are computed using the GHK

(Geweke-Hajivassiliou-Keane) simulation method in Limdep 9.0 (Greene, 2007). The approximation is based on averaging the values of the simulated probabilities from random draws (taken from upper-truncated standard normal distributions) in each replication (we used 200 random draws).

The procedure to obtain the final BVP models was as follows. For each attribute, we explored significant relationships individually for the two types of ANA behaviour (SNA and INA). Then, multiple-predictors models were explored simultaneously, using the criteria of significance and substantiality (of parameters) together with parsimony to select the final model for each attribute. Thus, the final models were designed to contain the most significant predictors while also looking to include different kind of predictors (if relevant) such as farm characteristics and management, farmer profile and attitudes and farmer status quo regarding the fulfilment of the AES requisites.

3 Data

3.1. Case Study and Attributes

The data are sourced from a CE survey of olive farmers in Andalusia, Spain. Olive trees are the main crop grown in the region, covering more than 1.5 million hectares or 48% of the total farmland. Olive grove systems have great potential for improvement in the provision of ES, especially those related to biodiversity, soil fertility, mitigation of climate change, and scenery (Villanueva *et al.*, 2014). This was the motivation for the original research into the implementation of AES aimed at increasing the provision of these ES; hence the need for appropriately-designed CE attributes.

Table 1 describes the six attributes used in the CE. Three attributes were linked to agricultural management, two attributes to policy design and an additional attribute specifies the level of compensation payments. For a detailed description of the attributes, we refer the reader to Villanueva *et al.* (2015).

Table 1 about here

3.2. Experimental Design and Data Collection

A fractional factorial design that is optimal in the differences (Street and Burgess, 2007) was used to create a manageable number of choice sets, reducing the number of total possible combinations from 1924 to 192 profiles (D-efficiency=91.3%). These choice sets were divided into 24 blocks of eight choice sets each, with each farmer answering one block. Each choice set included two alternatives of AES and a status quo alternative, representing non-participation.

After thorough pre-testing, the questionnaire included four sets of questions addressing: i) farm characteristics, ii) farmer characteristics, iii) choice sets, and iv) farmers' knowledge of and attitudes toward the implementation of AES in olive growing. An explanation of the attributes and the choice set was provided to farmers prior to completing the choice sets. An open-ended question format was used to collect information on reasons for serial non-participation to identify protest beliefs.

A multi-stage cluster sampling procedure was employed. In the first stage, five agricultural districts in Andalusia were selected randomly and then 10 villages/towns as secondary sampling units. Finally, in each village, between six and eight face-to-face interviews were conducted, singling out farmers in various locations following a random route procedure. The interviews were carried out between October 2013 and January 2014, and produced 327 complete responses.

4 Results

4.1. Modelling Results

Out of the total number of complete responses, 67 were serial non-participants (i.e. always chose the status quo alternative). Although they were scrutinised using debriefing questions (to distinguish protesters from very high takers), we focus the analysis on the respondents whose responses explicitly showed that they made trade-offs between the attributes and the attribute levels –i.e. those who did not always chose the status quo. Thus 261 responses were included in the analysis.

Table 2 reports the share of respondents who did not attend to each attribute according to self-reported non-attendance (SNA) and non-attendance inferred using the HHA (INA). For all the attributes, the level of non-attendance is higher for SNA than for INA. For both approaches, Payment (PAYM) is the attribute with the lowest level of non-attendance (18.77% and 6.13% of the respondents ignored to this attribute for SNA and INA, respectively). For both SNA and INA, the attribute with the highest level of non-attendance is MONI (with 81.40% and 68.96% respectively), with the second most-ignored attribute being COLLE (54.41%) for SNA and EFA (21.84%) for INA. We can compare these results with Espinosa-Goded and Barreiro-Hurlé (2010), who, using the SNA approach, found that the lowest level of non-attendance relates to the yearly payment attribute (1%) with the corresponding values for the remaining attributes ranging between 19% and 67%. Also, Greiner (2016) reports that the farmers in her sample pointed to the monitoring attribute as the least attended to when making their choice decisions, yielding a much lower score (she uses a Likert scale) than the other attributes.

Table 2 about here

Table 3 shows the three EC_MXL models included in the analysis: the base model not accounting for ANA (MXL_Base) and the two models that do account for ANA, using respondents' statements (MXL_SNA) and HHA (MXL_INA) (in the case of the latter two models, differentiating parameters of both utility functions, i.e., for those who attended to –*attendance*-A– and ignored –*non-attendance*-NA– the attributes). The three models are highly significant and show remarkable goodness-of-fit, although the models accounting for ANA clearly outperform the base model (registering better LL ratio, Pseudo R^2, AIC/N, and BIC/N). All the attribute parameters are highly significant (most of them at the 0.1% level) and have the expected sign. The only exceptions are: the parameters of the MONI attribute, which are not significant in any of the models considered (except for the MXL_INA in the attendance group); the parameters of the CCMA and COLLE attributes in the non-attendance group for the MXL_SNA (significant at the 10% level); and, most notably, the non-attendance utility function of the MXL_INA model, which registers no significant mean parameters for any of the attributes. On the other hand, it is worth remarking that the parameter differences between the utility functions of the two attendance groups (MXL_SNA and MXL_INA) are all, with the exception of CCMA, very small.

With regards to heterogeneity, unlike the attendance groups, the non-attendance groups report a standard deviation parameter that is not significant. Accordingly, all their parameters –except PAYM for the MXL-SNA– were set as fixed parameters, following the approach used by Hess and Hensher (2010). The parameter of the constant (ASC_{SQ}) is negative and significantly different from zero for the three models, indicating unobserved sources of heterogeneity that explain farmers' preferences towards AES. The error component associated with the AES alternatives is significant for the three models, implying that it efficiently captures the 'status quo effect'.

Table 3 about here

Observing the results shown in Table 3, it is clear that the attribute MONI received the least attention from the farmers, indicating that monitoring played a minor role in their choices. These results are similar to those of Greiner (2016), who finds the monitoring attribute to be not significant; they differ, however, from those of Broch and Vedel (2012), who find that the monitoring attribute determines farmers' willingness to participate in AES. The informal information collected during the survey suggests that two contrasting reasons could be behind these results, namely, the willingness to comply with the requirements and the adoption of strategic behaviour linked to moral hazard (Villanueva *et al.*, 2015). We consider that the substantial amount of noise around this attribute suggests that it should be excluded from the ANA analysis; hence, we focus the analysis on the remaining five attributes.

Table 4 shows the differences between the mean parameters of the attendance and non-attendance groups for the MXL_SNA and MXL_INA models. As shown in the table, the mean parameter values for the non-attendance group of the sample are much lower than those for the attendance group, showing significant differences in all cases for both models. Logically, considering all the attributes conjointly, the null hypothesis of parameter equality across the two subgroups is rejected. Therefore, the results shown in Tables 3 and 4 –especially the different levels of significance for attribute parameters and the remarkable difference in their absolute values, along with the different heterogeneity patterns– indicate a strong difference in the utility functions of attendance and non-attendance groups of respondents.

Table 4 about here

4.2. Comparison Between SNA and INA: ANA Concordance and the Impact on Welfare Estimates

Table 5 shows the level of concordance between SNA and INA. As shown in the table, the level of concordance ranges from 56% for the COLLE attribute to 79% for the payment attribute (the average level for the five attributes is 64%). It is worth noting that the average level of concordance between SNA and INA is around 76% if we focus only on attendance groups, whereas a lower level of concordance (45% on average) is found for non-attendance groups. This points to a higher level of unreliability when individuals state their non-attendance compared to when they state their attendance.

Analysing the individual ANA strategies stated by farmers (SNA) and inferred analytically (INA), results show that the SNA patterns vary more widely than the INA ones, hinting at higher heterogeneity of ANA strategies. In this vein, the percentage of full attendance stated by the farmers was significantly lower (6.5%) than that inferred by the HHA (39.1%). If we add patterns with 4 attributes attended to, then the percentage grows to 34.5% and 80.1% for SNA and INA, respectively. Models predicted full non-attendance for 1.1% of farmers for SNA, whereas no farmer was predicted as full non-attendance for INA. Additionally, the percentage of concordance between the two approaches taking into account the whole set of patterns (individual full profile approach) is 12%, a value which should not be seen as negligible considering the number of attributes and the high level of heterogeneity of SNA patterns.

Table 5 about here

Table 6 shows the estimates of WTA for the base, SNA and INA models. When accounting for ANA (i.e. using the parameters of the attendance group of the MXL_SNA and MXL_INA models), we find moderate-to-low departures from the WTA estimated without accounting for it (see the MXL_Base model). For SNA, the relative deviations from the base model range from 17% to 24%, except for CCMA which registers a 44% deviation. For INA, CCAR shows the only noticeable deviation at 16%, with the remaining attributes showing deviations lower than 7%. However, the results of the Poe *et al.* (2005) test show significant differences between mean parameters for SNA compared to the base model only for the attribute CCMA, while no significant differences at all are found for INA.

Table 6 about here

5 Discussion and Conclusions

While discontinuous preferences have been systematically investigated in environmental valuation assessments using WTP formats, there are virtually no studies that explore this topic in analyses focusing on ES providers' preferences towards incentive-based schemes. Although there is a growing body of literature in this field, to the best of our knowledge, our study and that of Espinosa-Goded and Barreiro-Hurlé (2010) are the only two studies which systematically account for ANA behaviour in an analysis of ES providers' WTA; moreover, our study is the first of this type to compare stated and inferred ANA approaches.

As in Espinosa-Goded and Barreiro-Hurlé (2010), and many demand-side environmental valuation studies, we find ANA behaviour in respondents' choices, with a low number of respondents attending to all the attributes. Regardless of the ANA approach (stated or inferred) applied, the monetary attribute registers the lowest level of non-attendance, which also mirrors Espinosa-Goded and Barreiro-Hurlé (2010)'s results. The low level of non-attendance to the monetary attribute reported in this study and that of Espinosa-Goded and Barreiro-Hurlé on ES providers' WTA may contrast with demand-side environmental valuation studies, which report much higher levels (e.g. 90%, 61%, and 39% for Scarpa et al., 2009; Campbell et al., 2011; Kragt, 2013, respectively). The different valuation framework, with farmers deciding whether or not to adopt certain environmentally-friendly practices (usually involving opportunity costs) depending on the compensation offered, seems to explain this markedly different level of non-attendance to the monetary attribute.

With regards to non-monetary attributes, we find discrepancies in the level of non-attendance between the two ANA approaches, with the inferred approach showing a lower level of non-attendance than the stated approach. Regardless of the approach, the very high non-attendance to the monitoring attribute should be seen more as the consequence of the unexpected result of the very low importance of the attribute. For the other non-monetary attributes, it seems that, when asked, farmers overstate their level of non-attendance to attributes, maybe as a result of applying a heuristic process in which they overrate the importance of some attributes over others in their choices. This is in line with Alemu *et al.* (2012), who suggest that individuals' ex-post rationalisation may differ from their ex-ante behavioural processing of the choice sets. We believe that the higher number of ANA patterns shown for the stated approach compared to the inferred approach is in keeping with this rationale. Also, as advocated by Hess *et al.* (2012), there is a possibility that farmers do not in fact ignore an attribute, but simply show lower intensity of preferences related to it. In this regard, instead of questioning farmers at the end of the choice sets, deeper insights may be gained by questioning them about their attribute attendance in each choice set.

By accounting for ANA, using either the stated or inferred approach, we achieve improvements in model fits compared to uncorrected models. The models accounting for ANA successfully capture the different behavioural patterns of the two groups of respondents (those who attend to the attributes and those who ignore them). This is evidenced by significant differences in marginal sensitivities and observed heterogeneity between the two groups, observed for both the stated and inferred approaches.

These results suggest that both approaches can be used to better model data from CE investigating ES providers' WTA for participating in incentive-based schemes. This finding has already been reported by previous studies on demand-side environmental valuation (Kragt, 2013, Weller *et al.*, 2014, among others), but this study is the first to show it in the context of supply-side environmental valuation. However, as is the case with the demand-side literature (see Alemu *et al.*, 2012, Colombo *et al.*, 2013, for a discussion), we have no conclusive results on the extent to which the inferred approach is better than the stated one, since both approaches show similar goodness-of-fit indicators (and parameter estimates) for our dataset. According to the level of significance of attribute parameters reported in our study, it can be argued that the inferred ANA approach is better able to discriminate between attendance and non-attendance groups of respondents. However, this does not necessarily mean that it represents a 'better' approach, as it may well not capture attributes with low importance (i.e. confounding ANA with them and wrongly setting parameters to zero, as suggested by Hess *et al.*, 2012). The stated ANA approach, on the other hand, may be slightly better at capturing these attributes, given that some significant attribute parameters for the non-attendance group of respondents are obtained in our study (and in Espinosa-Goded and Barreiro-Hurlé, 2010, as well).

Although we find that models accounting for ANA outperform those that do not account for it, our results regarding WTA estimates show little to no significant differences. These results would suggest that the failure to address ANA in these types of studies may not have produced the large impacts on welfare estimates reported for demand-side WTP contexts. However, we report non-negligible deviations, all of them positive and with one attribute out of four showing significant differences, implying that by not accounting for ANA analysts may provide erroneous signals to policy makers (especially by suggesting implementation budgets that are too low). Therefore, we consider that further research is still needed to establish the extent to which, and under what circumstances, WTA estimates may be notably impacted (or not) by ANA behaviour.

We provide some insights into the explanations for ANA behaviour by jointly modelling stated and inferred ANA. Our results show a wide variety of variables influencing non-attendance to attributes, including farmers' status quo, farm characteristics and management, farmer characteristics and attitudes, perceptions and knowledge. Some variables have previously been reported as predictors of farmers' ANA behaviour in this type of WTA study (Espinosa-Goded and Barreiro-Hurlé, 2010), while most of them relate to variables previously identified as determinants of scheme adoption (Siebert *et al.*, 2006, Uthes and Matzdorf, 2013). Overall, our results hint at a positive relationship between ease of scheme adoption and non-attendance to attributes. The rationale behind this may be that farmers consider attributes (scheme requirements) and levels to be of lesser importance if they find that they already comply to a large extent with the requirements included in the scheme. It is worth noting that the different individuals' status quo level –and its obvious impact on welfare estimates– is something rarely reported in demand-side environmental valuation studies. Conversely, although a consideration of the different individuals' status quo is, in theory, common in studies analysing ES providers' WTA, we find that it is not yet sufficiently acknowledged, with most such studies failing to collect and report information on the different providers' status quo. Thus, we strongly recommend collecting information about individuals' status quo in this type of study, and including it in the analysis. Finally, with regards to identifying predictors for stated and inferred ANA, our results do not show clear commonalities or dissimilarities which would shed light on the different behavioural rationale behind them. Clearly, further research is needed to understand what factors explain ANA behaviour in these WTA contexts.

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Table 1
Attributes and levels used in the choice set design.

Attribute [Acronym]	Explanation	Levels
Cover crops area [CCAR]	Percentage of the olive grove area covered by cover crops	- 25% - 50%
Cover crops mana-gement [CCMA]	Farmer's management of the cover crops	- Free - Restrictive management
Ecological focus areas [EFA]	Percentage of the olive grove plots covered by ecological focus areas	- 0% - 2%
Collective participation [COLLE]	Participation of a group of farmers (at least 5) with farms located in the same municipality	- Individual participation - Collective participation
Monitoring [MONI]	Percentage of farms monitored each year	- 5% - 20%
Payment [PAYM]	Yearly payment per ha for a 5-year AES contract	- €100/ha per year - €200/ha per year - €300/ha per year - €400/ha per year

Table 2
Share of attribute non-attendance for stated (SNA) and inferred (INA) non-attendance approaches.

Attribute	Stated	Inferred
Cover crops area [CCAR]	45.59	18.77
Cover crops management [CCMA]	48.28	18.39
Ecological focus areas [EFA]	40.23	21.84
Collective participation [COLLE]	54.41	19.54
Monitoring [MONI]	81.40	68.96
Payment [PAYM]	18.77	6.13

Table 3
MXL reference model (MXL_Base), and stated (MXL_SNA) and inferred (MXL_INA) non-attendance MXL models.

	Coeff.	MXL_Base		MXL_SNA				MXL_INA			
				Attendance (A)		Non-attend. (NA)		Attendance (A)		Non-attend. (NA)	
		Est.	*SE*	*Est.*	*SE*	*Est.*	*SE*	*Est.*	*SE*	*Est.*	SE
Mean parameters											
CCAR	μ_1	-0.085***	0.010	-0.155***	0.015	-0.014*	0.007	-0.147***	0.014	0.052	0.040
CCMA	μ_2	-2.689***	0.259	-6.587***	0.651	-0.351^{Ŧ}	0.186	-4.822***	0.412	0.911	0.709
EFA	μ_3	-0.876***	0.100	-1.986***	0.213	-0.176*	0.079	-1.824***	0.171	0.408	0.298
COLLE	μ_4	-2.298***	0.257	-3.860***	0.392	-0.442^{Ŧ}	0.239	-3.820***	0.386	0.833	0.811
MONI	μ_5	-0.015	0.009	-0.028	0.016	-0.009	0.010	-0.045***	0.014	-0.015	0.010
PAYM	μ_6	0.018***	0.001	0.023***	0.001	0.007***	0.002	0.024***	0.002	-0.003	0.003
ASC_SQ	$\delta_{\_SQ}$	-0.801**	0.351	-1.719***	0.377	--	--	-0.958***	0.344		
Standard deviation of random parameters											
CCAR	σ_1	0.108***	0.012	0.144***	0.018	--	--	0.137***	0.014	--	--
CCMA	σ_2	3.284***	0.331	4.915***	0.493	--	--	4.459***	0.449	--	--
EFA	σ_3	1.143***	0.117	1.615***	0.226	--	--	1.600***	0.139	--	--
COLLE	σ_4	2.789***	0.255	3.604***	0.393	--	--	3.380***	0.350	--	--
MONI	σ_5	--	--	--	--	--	--	--	--	--	--
PAYM	σ_6	0.018***	0.001	0.023***	0.001	0.007***	0.002	0.024***	0.002	--	--
Error comp.	H	2.751***	0.296	3.220***	0.327			2.875***	0.416		
Log-Likelihood			-1367.9				-1081.1				-1089.4
K Parameters			12				19				19
Pseudo R^2			0.403				0.514				0.525
AIC/N			1.322				1.065				1.060
BIC/N			1.356				1.109				1.109

***, **, *, ^{Ŧ} indicate significance at the 0.1%, 1%, 5%, and 10% levels respectively.

Table 4
Improvements in model performance considering non-attendance behaviour and differences between attendance and non-attendance groups using models accounting for non-attendance (MXL_SNA and MXL_INA).

Attributes	Coeff.	MXL_SNA			MXL_INA		
		μ_A- μ_{NA}[a]	LL test[b]	Asy. t[c]	μ_A- μ_{NA}[a]	LL test[b]	Asy. t[c]
CCAR	μ^1	-0.141	115.131***	-8.60***	-0.198	128.095***	-4.63***
CCMA	μ^2	-6.236	174.662***	-9.30***	-5.733	141.975***	-6.97***
EFA	μ^3	-1.810	126.364***	-7.96***	-2.232	144.308***	-6.65***
COLLE	μ^4	-3.417	87.378***	-7.51***	-4.653	140.076***	-5.12***
PAYM	μ^6	0.015	74.619***	7.95***	0.027	100.741***	8.45***
Overall	All		573.426***			557.325***	

[a] μ_A- μ_{NA} is the difference between mean attribute parameters for attendance (A) and non-attendance (NA) groups.
[b] The log-likelihood ratio test was employed to test for statistically significant model improvements, where the log-likelihood of the base model is compared with the log-likelihoods of the MXL_SNA and MXL_INA models for the whole set of parameters: ($-2[LL_{\text{Base model}} - LL_{\text{ANA model}}] \sim X^2$) and the log-likelihoods of the MXL_SNA and MXL_INA models are compared with log-likelihoods of the same models when ignoring the NA behaviour for each parameter individually.
[c] The Delta method was employed to test for statistical differences between attendance and non-attendance groups (see Asy. t).

Table 5
Level of concordance (in percentages) between stated (SNA) and inferred (INA) non-attendance patterns.

Attribute		SNA		Total concordance
		Attendance	*Non-attendance*	(SNA-INA)
CCAR				
INA	Attendance	46.36	32.18	
	Non-attendance	8.05	13.41	
Total				59.77
CCMA				
INA	Attendance	46.74	34.87	
	Non-attendance	4.98	13.41	
Total				60.15
EFA				
INA	Attendance	52.49	25.67	
	Non-attendance	7.28	14.56	
Total				67.05
COLLE				
INA	Attendance	41.00	39.46	
	Non-attendance	4.60	14.94	
Total				55.94
PAYM				
INA	Attendance	77.01	16.86	
	Non-attendance	4.21	1.92	
Total				78.93

Table 6
Willingness to accept (WTA) estimates for the models considered[a].

Attributes	MXL_Base	MXL_SNA	MXL_INA
CCAR	4.84	5.66	5.63
	(3.77 – 5.83)	(4.30 – 7.43)	(4.80 – 6.46)
CCMA	153.44	221.07[†]	158.81
	(128.44 – 180.81)	(176.45 – 287.29)	(134.28 – 185.23)
EFA	49.97	62.09	53.24
	(38.94 – 61.28)	(47.48 – 80.69)	(44.64 – 62.93)
COLLE	129.98	152.77	133.61
	(106.08 – 155.99)	(119.75 – 197.28)	(114.11 – 154.10)

[a] All WTA estimates are different from zero at the 0.1% significance level. The Poe *et al.* (2005) test was used to check for significant differences, with the attribute CCMA (see superscript [†]) being the only one showing significant differences at the 95% level (Bonferroni correction was employed to keep the Type I error at 5% level) between WTA estimates for SNA compared to the base approach.