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Unraveling determinants of inferred and stated attribute non-attendance: effects on farmers' willingness to accept to join agri-environmental schemes

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ABSTRACT: *Attribute non-attendance (ANA) has received very little attention in the context of willingness to accept (WTA), although an increasing number of studies analyze the preferences of ecosystem service providers towards incentive-based schemes. We add to the understanding of ANA behavior by analyzing stated and inferred ANA in a choice experiment investigating farmers' WTA for participating in agri-environmental schemes (AES) in southern Spain. We use mixed logit models, following Hess and Hensher (2010) for the inferred ANA approach. Evidence is found of ANA behavior 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. WTA estimates are only moderately affected, which to some extent is consistent with the low level of non-attendance found for the monetary attribute. Stated and inferred approaches show very similar WTA estimates. Additionally, we investigate sources of observed heterogeneity related to ANA behavior by using a sequence of bivariate probit models for each attribute. Overall, our results hint at a positive relationship between ease of scheme adoption and non-attendance to attributes. However, further research is still needed in this field.*

Keywords: *Choice experiments; Discontinuous preferences; Inferred attribute non-attendance; Agri-environmental schemes; Payments for ecosystem services.*

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 maximizers. As a result, the choice of the preferred alternative should reflect fully compensatory behavior (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, Campbell et al 2008, Colombo and Glenk 2013). An additional factor is the presence of bounded rationality, which refers to individuals adapting their behavior 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 behavior 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 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 modeling respondents' preferences including ANA in an attempt to limit potential biases in welfare estimates (see Leong and Hensher 2012, for a review). For instance, some authors use self-reported information on respondents' attendance (i.e., *stated attribute attendance*) (e.g., Campbell et al 2008, Carlsson et al 2010, Hole 2011, Scarpa et al 2013, Chalak et al 2016). Others control ANA by inferring from the CE data (i.e., *inferred attribute attendance*) (e.g., Scarpa et al 2009, Campbell et al 2011, Colombo et al 2016, Caputo et al 2013, Hole et al 2013). Alemu et al (2012), Kragt (2013), Scarpa et al (2013), and Ortega and Ward (2016) compare these two approaches finding that there is little concordance between them. In addition, several works focus on the relationship between ANA and other issues associated with CE applications. These include the effect of elements such as CE design features (e.g., number of choice sets, alternatives, attributes, and levels) (Weller et al 2014), respondents' knowledge about the topic analyzed (Sandorf et al 2016), choice inconsistencies (Colombo et al 2016), cost thresholds and cut-offs (Campbell et al 2012), ranking and non-attendance data (Chalak et al 2016), and serial and choice set attribute non-attendance (Scarpa et al 2010), on the degree to which respondents ignore attributes, endogeneity (Hole et al 2016, Collins 2012), and different treatments for scale variation (Scarpa et al 2010, Balcombe et al 2015, Campbell et al 2011, Thiene et al 2015).

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 analyze the preferences of ecosystem service (ES) providers towards incentive-based schemes (Villanueva et al 2017a, Colen et al 2016). 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. Especially abundant are those studies focused on farmers' and foresters' preferences towards payment for ecosystem service schemes (PES) (Peterson et al 2015, Vedel et al 2015, Costedoat et al 2016) and agri-environmental schemes (AES) (Espinosa-Goded et al 2010, Christensen et al 2011, Broch and Vedel 2012). 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 (Greiner 2016, Kassahun and Jacobsen 2015), 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 novel insights into ANA in this context by using both stated and inferred approaches and exploring the concordance between the two.

We analyze farmers' ANA behavior, 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 (HHA) was used for inferred preference attendance. Our empirical application is not intended to assess alternative methodological approaches developed to deal with the wide array of potential attribute processing strategies (Payne et al 1993), but rather to find a suitable and flexible approach which would allow an evaluation of the potential impact on taste heterogeneity and WTA estimates. For this purpose, we use mixed logit models to analyze 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. Other novelties of the paper worthy of mention relate to the estimation of welfare measures, together with the investigation of sources of observed heterogeneity, which can be potential predictors of stated and inferred ANA behaviors.

METHOD

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 behavior 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.

The MXL 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 (Train 2003). 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 (EC) with standard deviation denoted by η (constant fixed effect for the no-enrolment alternative) (Scarpa et al 2005).

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.

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. 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 has been identified through self-reported statements, the ANA behavior is accounted for by restricting the corresponding attribute coefficient to zero in the utility functions if respondents did in fact really ignore an attribute (Hensher et al 2012). Essentially, this means that there may be different zero restrictions imposed for each respondent. Thus, the model output will have two layers of separate parameter estimates in order to simultaneously address attendance and non-attendance behaviors in such a way that, when a respondent states non-attendance, the corresponding parameters will be zero for the attendance layer and freely estimated for the non-attendance layer (and vice versa). This approach has emerged as an efficient way to model attribute processing strategies (Hess and Hensher 2010) in contrast with setting the corresponding attributes (instead of the parameters) to zero, estimating only the parameters associated with the attendance layer (Kragt 2013) or, as mentioned above, exploring the heterogeneity around the mean parameters (Espinosa-Goded and Barreiro-Hurlé 2010).

For INA, the two-stage approach proposed by Hess and Hensher (2010) (HHA) was followed. The first stage involves the stochastic identification of respondents showing ANA behavior. Thus, 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. In the second stage, the ANA behavior is modeled by allowing the estimation of separate parameters, as mentioned above, for attendance and non-attendance response patterns. Thus, as with the SNA approach, the utility function is split into two for attendance and non-attendance, to restrict the attribute coefficients to zero if an attribute was ignored (Hess and Hensher 2010).

Testing Potential Confounding Effects Related to Experimental Design[1]

The inferred HHA could be affected by confounding effects between real ANA patterns and behaviorally equivalent responses generated by the particular features of the experimental design in question. Thus, the role played by the experimental design, which is exogenous to the respondent's choice behavior, should be evaluated to confirm that there is little or no presence of confounding effects. To do that, ordinary linear regressions were run to determine the extent to which experimental design features regarding the sequence of choices could systematically produce high or low CVs. As a diagnostic test, the CVs for each attribute were regressed on dummy variable indicators of the experimental design blocks. If these indicators prove to be significant and have notable explanatory power in terms of R^2, then it can be demonstrated that some of the observed variation in CV is

[1] We thank the anonymous reviewer for having suggested this part.

attributable to the experimental design, and thus not related to genuine ANA behavior. Also, kernel density plots were estimated to graphically represent the dispersion of the CV for each random parameter.

Concordance and WTA Estimates

The concordance between SNA and INA was analyzed 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 between ANA patterns for the two approaches was checked at the individual level (Scarpa et al 2013), 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 unconditional WTA for the population was estimated by applying the Total Probability Theorem. There are two groups with coefficients and binomial probability of ANA for one non-monetary attribute, and two more groups with binomial probability for the monetary attribute. As the two probabilities are independent, the joint probability is the product of the two:

$$WTA = -\begin{bmatrix} \left(\frac{\mu_{ANA_{NMi}}}{\mu_{ANA_M}}\right) \times \left(P_{ANA_{NMi}} \times P_{ANA_M}\right) + \left(\frac{\mu_{AA_{NMi}}}{\mu_{ANA_M}}\right) \times \left(P_{AA_{NMi}} \times P_{ANA_M}\right) + \\ \left(\frac{\mu_{ANA_{NMi}}}{\mu_{AA_M}}\right) \times \left(P_{ANA_{NMi}} \times P_{AA_M}\right) + \left(\frac{\mu_{AA_{NMi}}}{\mu_{AA_M}}\right) \times \left(P_{AA_{NMi}} \times P_{AA_M}\right) \end{bmatrix} \quad (5)$$

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) uses the variance-covariance matrix to estimate confidence intervals for elasticities, through a Monte Carlo simulation. It has been widely used for the case of marginal WTA/WTP (Bliemer and Rose 2013). Specifically, to estimate each WTA in the context of an EC_MXL, the uncertainty (standard errors) attached to the structural parameters of the distributions (i.e., the mean and standard deviation) are considered. Thus, the Krinsky and Robb procedure for WTA estimation involves taking simulated draws for each of the estimated structural parameters. From the resulting distributions, simulated draws can be taken and the ratios computed (for an extensive description, see Hensher and Greene 2003).

To test for equality between the WTA estimates for the three alternative approaches applied (not accounting for ANA, or Base; SNA; and INA), the Complete Combinatorial (CC) test suggested by Poe et al (2005) was used. Based on the three distributions of WTA estimates derived from the Krinsky and Robb procedure, the CC estimates all the differences of elements contained in two distributions to check for statistical difference (the difference vectors between each pair of WTA were estimated). The significance levels of the WTA differences were derived by assessing the value of the resulting cumulative distributions of the three difference vectors per attribute (the p-value thus indicates the degree of non-overlap in a single vector component). As three comparisons were made per attribute, a Bonferroni correction was employed to keep the Type I error at the 5% level. Therefore, the following three hypotheses were tested per attribute:

$H0_1$: WTA_k Base = WTA_k SNA ; HA_1: WTA_k Base ≠ WTA_k SNA

$H0_2$: WTA_k Base = WTA_k INA ; HA_2: WTA_k Base ≠ WTA_k INA

$H0_3$: WTA_k SNA = WTA_k INA ; HA_3: WTA_k SNA ≠ WTA_k INA

Uncovering the Sources of Observed Heterogeneity behind ANA Behavior

To uncover the sources of observed heterogeneity that could be behind ANA behavior, a sequence of bivariate probit models (BVP) for each attribute was 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[2]. 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):

$$y_{im}^* = B_m' x_{im} + \varepsilon_{im} \; (m = 1, \dots, \mathrm{M})$$
$$y_{im} = \begin{Bmatrix} 1 \text{ if } y_{im}^* > 0 \\ 0 \text{ otherwise} \end{Bmatrix} \qquad (6)$$

where, in our case, m=1,2 denoting the two types of ANA behavior (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 behavior for each AES attribute, X_{im}, as well as unobserved characteristics captured by the stochastic error term ε_{im} (Chib and Greenberg 1998). 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)).

[2] This econometrical approach is similar to the Seemingly Unrelated Regression Equations (SURE) model but with the distinctive feature that the nature of the dependent variables is binomial.

As the variance-covariance matrix of ε_{im} in Eq. (6) includes potentially non-zero correlation off the main diagonal, the ε_{im} jointly follow a multivariate normal (MVN) distribution:

$$(\varepsilon_{i1}, \varepsilon_{i2})' \sim MVN\left(0, \begin{bmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{bmatrix}\right) \quad (7)$$

where ρ_{jm} is the correlation coefficient of ε_j and ε_m for $j \neq m$. 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). For a detailed explanation of the procedure see Cappellari and Jenkins (2003).

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 behavior (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 fulfillment of the AES requisites.

DATA

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), all of which are in high demand in European (EC 2010) and Andalusian (Rodríguez-Entrena et al 2012) societies. 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 specifying the level of compensation payments. For a detailed description of the attributes, we refer the reader to Villanueva et al (2015).

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 management [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

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%)[3]. These choice sets were divided into 24 balanced blocks of eight choice sets each, with each farmer answering one block[4]. Each choice set included two alternatives of AES and a status quo alternative, representing non-participation. Appendix A shows an example of a choice set.

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

[3] Following Scarpa and Rose (2008), our experimental design was evaluated ex-post in terms of D-error for the multinomial logit (MNL) model estimated from our data. While the D-error of our design is 0.0048, it decreases to 0.001 for an efficient design calculated using our ex-post priors, for the same number of profiles and blocks of our design.

[4] The choice task positions in the sequence were not rotated by respondent, nor were there alternative positions in the choice cards. In this regard, our previous experience with farmers made it advisable to keep the choice experiment as simple as possible. In any case, we do not expect this to have a strong effect as the interviewers were carefully trained to remind the respondents that each choice task was independent from the others and the three alternatives in play, so they very likely stated their sincere preferences.

327 complete responses. In terms of key farm characteristics (size and average yield), as well as farmers' features (age, level of education and farm-labor time), the sample mirrors farm characteristics obtained in a previous benchmarking survey carried out by Gómez-Limón and Arriaza (2011), who defined farm in the same way as in this study[5]. With respect to size, large farms seem to be slightly overrepresented relative to the benchmarking survey, although this may be explained by the on-going structural changes in the region.

RESULTS

Modeling 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 scrutinized 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[6]. 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%)[7] 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.

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[5] In our study, as in theirs, a farm is defined as a single decision-making entity regardless of its legal nature; there is no available register of farms defined as such and so we cannot compare our sample to the official statistics. To compare the characteristics of our sample to that of Gómez-Limón and Arriaza (2011), we ran unpaired t-tests (χ^2 for dichotomous variables).

[6] It is arguable that very high takers (i.e., non-protest responses) also made trade-offs among the alternatives offered but we decided not to include them in the analysis as the line which separates these respondents from protesters is blurred. Thus, our analysis does not include those respondents who ignore attributes due to protest behaviour, as suggested by Alemu et al (2012). We refer readers interested in the issue of protest responses in studies investigating ES providers' WTA to Villanueva et al (2017a).

[7] It could be argued that the very low level of non-attendance to the monetary attribute found by Espinosa-Goded and Barreiro-Hurlé (2010) stems from the low profitability of the agricultural systems under study, characterised by high levels of extensification.

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 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.

With regards to heterogeneity, unlike the attendance groups, the non-attendance groups report insignificant standard deviation parameters. Accordingly, all their parameters –except PAYM for the MXL-SNA– were set as fixed parameters, following the approach used by Hess and Hensher (2010)[8]. 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[9]. The error component associated with the AES alternatives is significant for the three models, implying that it efficiently captures the 'status quo effect'.

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 insignificant[10]; they differ, however, from those of Broch

[8] Models with all the parameters estimated as random parameters are available upon request.

[9] The negative ASC_{SQ} may mean that farmers would waive some of the compensation associated with AES participation for reasons unrelated to the attributes.

[10] She investigates farmers' preferences towards the type of monitoring (self- vs. external monitoring) using first preference and best-worst RPL models, with the former approach being more similar to our base models. The monitoring attribute is found to be not significant when using the first preference RPL model, whereas it is significant with the best-worst model, albeit with a significance level lower than most of the other attributes.

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 behavior 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 3. MXL reference model (MXL_Base), and stated (MXL_SNA) and inferred (MXL_INA) non-attendance MXL models												
	MXL_Base				MXL_SNA				MXL_INA			
	Mean (μ)		SD (σ)		Mean (μ)		SD (σ)		Mean (μ)		SD (σ)	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Attendance (A)												
CCAR	-0.085***	0.010	0.108***	0.012	-0.155***	0.015	0.144***	0.018	-0.147***	0.014	0.137***	0.014
CCMA	-2.689***	0.259	3.284***	0.331	-6.587***	0.651	4.915***	0.493	-4.822***	0.412	4.459***	0.449
EFA	-0.876***	0.100	1.143***	0.117	-1.986***	0.213	1.615***	0.226	-1.824***	0.171	1.600***	0.139
COLLE	-2.298***	0.257	2.789***	0.255	-3.860***	0.392	3.604***	0.393	-3.820***	0.386	3.380***	0.350
MONI	-0.015	0.009	--	--	-0.028	0.016	--	--	-0.045***	0.014	--	--
PAYM	0.018***	0.001	0.018***	0.001	0.023***	0.001	0.023***	0.001	0.024***	0.002	0.024***	0.002
ASC_SQ	-0.801**	0.351	--	--	-1.719***	0.377	--	--	-0.958***	0.344	--	--
Non-attendance (NA)												
CCAR	--	--	--	--	-0.014*	0.007	--	--	0.052	0.040	--	--
CCMA	--	--	--	--	-0.351^{Ŧ}	0.186	--	--	0.911	0.709	--	--
EFA	--	--	--	--	-0.176*	0.079	--	--	0.408	0.298	--	--
COLLE	--	--	--	--	-0.442^{Ŧ}	0.239	--	--	0.833	0.811	--	--
MONI	--	--	--	--	-0.009	0.010	--	--	-0.015	0.010	--	--
PAYM	--	--	--	--	0.007***	0.002	0.007***	0.002	-0.003	0.003	--	--
Error comp. ($\eta_{\_nonSQ}$)	2.751***	0.296			3.220***	0.327			2.875***	0.416		
Log-Likelihood (LL)	-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			

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

Table 4 shows an evaluation of the differences between the mean parameters of the attendance and non-attendance groups for the MXL_SNA and MXL_INA models. The mean parameter values for the non-attendance group of the sample are much lower than those for the attendance group, so in all cases, the Delta method rejects the null hypothesis of parameter equality across the two subgroups (see the Asy. t parameters). Therefore, the results shown in Tables 3 and 4 indicate a strong dissimilarity in the utility functions of attendance and non-attendance groups of respondents. As shown in Table 4, this is in line with the differences in the goodness of fit criteria between the base (MXL_Base) and ANA models (MXL_SNA and MXL_INA), depicting substantial improvements when accounting for ANA.

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

Attributes	MXL_SNA		MXL_INA		Goodness of fit criteria	MXL_SNA vs MXL_Base[c]	MXL_INA vs MXL_Base[c]
	μ_A- μ_{NA}[a]	Asy. t[b]	μ_A- μ_{NA}[a]	Asy. t[b]			
CCAR	-0.141	-8.60***	-0.198	-4.63***	LL	286.8	278.5
CCMA	-6.236	-9.30***	-5.733	-6.97***	Pseudo – R2	0.111	0.122
EFA	-1.810	-7.96***	-2.232	-6.65***	AIC/N	0.247	0.262
COLLE	-3.417	-7.51***	-4.653	-5.12***	BIC/N	0.247	0.247
PAYM	0.015	7.95***	0.027	8.45***			

[a] μ_A- μ_{NA} is the difference between mean attribute parameters for attendance (A) and non-attendance (NA) groups.

[b] The Delta method was used to test for statistical differences between μ_A- μ_{NA} (see Asy. t).

[c] The differences in the goodness of fit criteria between the base model and the ANA models are displayed.

Testing potential confounding effects related to the experimental design

Table 5 displays the results related to the linear regressions run between the blocks of the experimental design and the CV for each parameter[11]. As indicated by the F-test, R-bar squared and the t-test, the experimental design in our case study does not represent a notable source of explanation for the coefficients of variation. Thus, there is no evidence of confounding effects between real ANA patterns and behaviorally equivalent responses generated by the particular features of the experimental design, since the observed variation in CV is not at all attributable to the experimental design.

Table 5. Results of the linear regressions between the blocks of the experimental design and the CV

Attribute	R-squared	Model test F (p-value)	R-bar squared	Coefficients for the blocks (dummy variables)
CCAR	0.098	0.32	0.011	Insignificant (p-value > 0.05)
CCMA	0.076	0.66	-0.012	Insignificant (p-value > 0.05)
EFA	0.069	0.76	-0.020	Insignificant (p-value > 0.05)
COLLE	0.109	0.19	0.023	Insignificant (p-value > 0.05)
PAYM	0.057	0.91	-0.034	Insignificant (p-value > 0.05)

[11] The regressions displayed in this table are an overview; the full output is available from the authors on request.

Appendix B displays the dispersion of the CVs for each parameter through kernel density plots, together with information on the quantiles of the posterior distribution of CV. In this regard, the widest distribution corresponds to COLLE and EFA attributes (being 3.84 and 4.75 the CV values at 0.90-quantile), while by far the narrowest is that of the PAYM attribute (CV=1.22 at 0.90-quantile). This finding regarding the COLLE and EFA seems reasonable since these attributes can generate a higher degree of uncertainty among the farmers. As they are not at all familiar with collective enrolment and are doubtful about the effects of EFA on their farm income, the non-attendance behavior may be more unpredictable. With regards to the distributions among attributes, there are no sharp distinctions, with only PAYM showing density concentrated below the threshold of 2. Thus regarding the PAYM attribute, there seems to be a lower degree of uncertainty, particularly due to the fact that farmers can compare payment levels with actual schemes.

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

Table 6 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.

Table 6. Level of concordance (in percentages) between stated (SNA) and inferred (INA) non-attendance patterns

Attribute		SNA Attendance	Non-attendance	Total concordance (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 7 shows 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 7. Patterns of attendance to AES attributes stated by the farmers (SNA) and inferred analytically (INA)

Attendance to attributes						SNA		INA	
Pattern	CCAR	CCMA	EFA	COLLE	PAYM	Freq.	%	Freq.	%
1	1	1	1	1	1	17	6.51	102	39.08
Sub-total 5 attributes						*17*	*6.51*	*102*	*39.08*
2	1	1	1	0	1	20	7.66	31	11.88
3	1	0	1	1	1	18	6.90	22	8.43
4	1	1	0	1	1	16	6.13	23	8.81
5	0	1	1	1	1	13	4.98	23	8.81
6	1	1	1	1	0	6	2.30	8	3.07
Sub-total 4 attributes						*73*	*27.97*	*107*	*41.00*
7	0	0	1	1	1	12	4.60	11	4.21
8	0	1	0	1	1	11	4.21	5	1.92
9	0	1	1	0	1	10	3.83	5	1.92
10	1	1	0	0	1	10	3.83	7	2.68
11	1	0	0	1	1	10	3.83	3	1.15
12	1	0	1	0	1	9	3.45	1	0.38
13	1	1	0	1	0	8	3.07	1	0.38
14	1	1	1	0	0	2	0.77	2	0.77
15	1	0	1	1	0	1	0.38	3	1.15
16	0	1	1	1	0	1	0.38	--	--
Sub-total 3 attributes						*74*	*28.35*	*38*	*14.56*
17	0	0	0	1	1	30	11.49	3	1.15
18	0	1	0	0	1	11	4.21	5	1.92
19	1	0	0	0	1	9	3.45	2	0.77
20	1	0	0	1	0	5	1.92	--	--
21	0	1	0	1	0	5	1.92	--	--
22	0	0	1	0	1	4	1.53	--	--
23	1	0	1	0	0	4	1.53	--	--
24	1	1	0	0	0	3	1.15	--	--
25	0	1	1	0	0	--	--	1	0.38
26	0	0	1	1	0	1	0.38	--	--

Table 7. Patterns of attendance to AES attributes stated by the farmers (SNA) and inferred analytically (INA) (*Cont.*)									
Attendance to attributes						SNA		INA	
Pattern	CCAR	CCMA	EFA	COLLE	PAYM	Freq.	%	Freq.	%
Sub-total 2 attributes						*72*	*27.58*	*11*	*4.22*
27	0	0	0	0	1	12	4.60	2	0.77
28	1	0	0	0	0	4	1.53	--	--
29	0	0	1	0	0	2	0.77	1	0.38
30	0	1	0	0	0	2	0.77	--	--
31	0	0	0	1	0	2	0.77	--	--
Sub-total 1 attributes						*22*	*8.44*	*3*	*1.15*
32	0	0	0	0	0	3	1.15	--	--
Sub-total 0 attributes						*3*	*1.15*	--	--
Total						261	100.00	261	100.00

Table 8 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 8. Willingness to accept (WTA) estimates for the models considered[a]			
Attributes	MXL_Base	MXL_SNA	MXL_INA
CCAR	4.84 (3.77 – 5.83)	5.66 (4.30 – 7.43)	5.63 (4.80 – 6.46)
CCMA	153.44 (128.44 – 180.81)	221.07[†] (176.45 – 287.29)	158.81 (134.28 – 185.23)
EFA	49.97 (38.94 – 61.28)	62.09 (47.48 – 80.69)	53.24 (44.64 – 62.93)
COLLE	129.98 (106.08 – 155.99)	152.77 (119.75 – 197.28)	133.61 (114.11 – 154.10)

[a] All WTA estimates are different from zero at the 0.1% significance level according to the Krinsky and Robb (1984) procedure. 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 between WTA estimates for SNA compared to the base approach.

Disentangling the Stated (SNA) and Inferred (INA) Non-Attendance Behaviors

We now turn to the results of the investigation on the potential predictors of the ANA behaviors. Tables 9 and 10 show the final BVP models that include the covariates representing predictors of SNA and INA for each attribute. The rho coefficient is significant in all four BVP models meaning that residuals of the expressions explaining the two dependent variables (i.e., non-attendance resulting from the SNA and INA approaches) are correlated. This supports the econometric assumption that the stated non-attendance is not independent of the inferred non-attendance, as it suggests that the BVP model is preferred over two separate probit models. The positive rho coefficients point to the existence of a relationship of complementary interdependence between the two approaches.

Regarding the sources of observed heterogeneity that explain ANA behavior, BVP models show that SNA and INA behaviors are influenced by different types of factors relating to the initial degree of compliance with AES requirements (category status quo), farm characteristics (ownership, location, irrigated area, physical features, etc.) and management (harvesting, soil management, etc.), farmer characteristics (professional training, level of education, age, etc.) and attitudes, perceptions and knowledge (especially with regards to the practices involved in the schemes). In this regard, the inter-attribute results indicated that these potential explanations for the ANA behavior are quite attribute-specific as most of the covariates only impact on one attribute. Only the following covariates represent predictors of ANA behavior for more than one attribute: *olive grove area owned* (for CCMA and EFA), *farmer not professionally trained* (for CCAR and EFA), *perception of cover crops as profitable* (for CCAR, CCMA, and COLLE), and *farmer knows the cover crop requisite within cross-compliance* (for CCMA and COLLE). The attribute-specificity of ANA predictors have also been highlighted by Espinosa-Goded and Barreiro-Hurlé (2010). However, apart from certain covariates found in both our study and theirs (namely ownership, irrigated area and previous experience in similar schemes, along with farmers' age, education level, professional training, and belonging to professional associations), we show a much wider variety of predictors of a different nature. In particular, our results show that the easier the scheme is to adopt (shown not only by status quo features but also by other farm and farmer characteristics which facilitate implementation, such as previous experience in similar schemes, professional training, positive perception of scheme requirements and farmers' knowledge about them, etc.), the higher the level of non-attendance. With regards to the comparison between predictors of SNA and INA, it is worth noting that we found a notably higher number of predictors for the former (20) than for the latter (14). Most of the predictors significantly explain one dependent variable (either SNA or INA), with only five predictors simultaneously explaining the two dependent variables. These predictors are *olive grove area owned* and *farmers comply with restrictive cover crops management* (for CCMA), and *olive grove area owned*, *irrigated olive grove area*, and *perception of EFA as environmentally beneficial* (for EFA). However, we do not find clear patterns of predictors explaining either one ANA approach or the other.

Table 9. Bivariate probit (BVP) models for the attributes CCAR and CCMA

		CCAR				CCMA			
		SNA		INA		SNA		INA	
		Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Covariate category	*Covariates*								
Status Quo	Farmers comply with CCAR-50% (% of farmers)	1.408 ***	0.254	0.223	0.265				
	Farmers comply with restrictive cover crops management (% of farmers)					1.398 ***	0.229	0.480 **	0.208
Farm characteristics and management	Olive grove area owned (% of farm olive grove area)					0.362	0.238	0.624 **	0.269
	Farm located in the Loma agricultural district (% of farmers)	-0.451 *	0.242	-0.519	0.333				
	Degree of slope (%)	-0.013	0.010	-0.037 ***	0.014				
	Tree density (olive trees per ha)					-0.002	0.002	-0.005 *	0.003
	Share of olives harvested from the ground above 10% of total olives harvested (1=Yes)	-0.431 **	0.191	-0.326	0.246				
	Participation in current AES (1=Yes)					1.175 ***	0.316	0.271	0.253
Farmer characteristics	Number of children (#)					-0.012	0.260	-0.503 **	0.249
	Farmer did not go to school (1=Yes)					0.563	0.411	0.597 *	0.312
	Farmer not professionally trained (1=Yes)	-0.348 *	0.181	-0.156	0.209				
	Farmer asks for advice at least once a month (1=Yes)	-0.368 **	0.181	-0.013	0.195				
Farmer attitudes and knowledge	Perception of cover crops as profitable (dimensionless, 1-5)	0.352 *	0.186	0.065	0.195	0.181 **	0.077	0.144 *	0.080
	Farmer knows the cover crops requisite within cross-compliance (1=Yes)					0.664 ***	0.205	0.235	0.228
Constant		0.173	0.203	-0.337	0.220	-1.795 ***	0.498	-1.317 **	0.584
Rho (1,2)		0.390 ***	0.109			0.333 **	0.134		
Log-likelihood function		-260.6				-225.8			
Inf. Cr. AIC		555				488.2			
Observations		244				242			

Significance: ***, **, * indicate significance at the 0.1%, 1%, and 5% levels respectively.

Table 10. Bivariate probit (BVP) models for the attributes EFA and COLLE

		EFA				COLLE			
		SNA		INA		SNA		INA	
		Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Covariate category	*Covariates*								
Status quo	Farmer complies with EFA-2% (1=Yes)	2.091 ***	0.461	0.091	0.226				
Farm characteristics and management	Olive grove area owned (% of farm olive grove area)	0.006 *	0.003	-0.008 ***	0.003				
	Irrigated olive grove area (% of farm olive grove area)	-0.008 ***	0.003	-0.007 **	0.003				
	Distance between olive trees lines (m)					0.070	0.044	0.106 *	0.058
	Presence of vegetated boundaries between farms (1=Yes)					-0.633 ***	0.231	0.109	0.254
	Workforce (Person-days per ha)					-0.018 **	0.008	0.007	0.009
	Belonging to integrated farming and/or irrigation associations (1=Yes)					0.216 *	0.126	0.128	0.140
Farmer characteristics	Farmer age (Years)	-0.016 *	0.009	0.001	0.008				
	Farmer not professionally trained (1=Yes)	-0.453 **	0.216	-0.059	0.199				
Farmer attitudes and knowledge	Perception of cover crops as profitable (dimensionless, 1-5)					0.034	0.200	-0.933 ***	0.232
	Perception of cover crops as environmentally beneficial (dimensionless, 1-5)					0.051	0.088	0.356 ***	0.128
	Farmer knows the cover crops requisite within cross-compliance (1=Yes)					-0.073	0.175	0.447 **	0.220
	Perception of EFA as environmentally beneficial (dimensionless, 1-5)	0.151 **	0.077	0.217 ***	0.078				
	Official controls generally detect irregularities when receiving CAP support (dimensionless, 1-5)					0.295 *	0.172	-0.076	0.202
Constant		-0.003	0.588	-0.699	0.509	-0.979	0.605	-3.364 ***	0.916
Rho (1,2)		0.212 *	0.126			0.640 ***	0.086		
Log-likelihood function		-263.1				-266.3			
Inf. Cr. AIC		556.2				570.7			
Observations		246				242			

Significance: ***, **, * indicate significance at the 0.1%, 1%, and 5% levels respectively.

DISCUSSION

In light of the general lack of studies investigating ANA behavior in analyses focusing on ES providers' preferences towards incentive-based schemes (with the only precedent being Espinosa-Goded and Barreiro-Hurlé 2010), we discuss the results by also referring to demand-side environmental valuation assessments. As in Espinosa-Goded and Barreiro-Hurlé (2010), and many demand-side environmental valuation studies (e.g., Campbell et al 2008, Scarpa et al 2009, Colombo et al 2016), we find ANA behavior 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, and Kragt 2013, respectively). The different valuation framework, with farmers facing a decision –usually familiar to them– on whether or not to change their business management by adopting 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. This likely results in a lower risk of incurring the typical biases encountered in demand-side valuation assessments, such as social desirability and yeah-saying (Loureiro and Lotade 2005, Balcombe et al 2011), which can have a very relevant effect in the context of environmental public goods valuation.

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 rationalization may differ from their ex-ante behavioral 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 a 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, as Scarpa et al (2010) and Ortega and Ward (2016) do. There may, however, be weak theoretical justification for such an approach (Balcombe et al 2015).

By accounting for ANA, using either the stated or inferred approach, model fits are improved compared to uncorrected models because these approaches successfully capture the different behavioral patterns of both attendance and non-attendance groups (evidenced by significant differences in marginal sensitivities and heterogeneity). This finding has already been reported in previous studies on demand-side environmental valuation (among others, see Kragt 2013, Weller et al 2014), but this study is the first to show such a result in the context of supply-side environmental valuation. However, as is the case with the demand-side literature (for a discussion, see Alemu et al 2012, Colombo et al 2013), 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 for our dataset. Yet, looking at the level of significance of attribute parameters (means and standard deviations) of the SNA and INA models (particularly regarding the non-attendance groups), it can be argued that the latter is better able to discriminate between attendance and non-attendance groups of respondents.

The above-mentioned finding hints at the creditable performance of HHA in modeling ANA behavior. However, we consider that this very much depends on the specific case under study. We find that this approach suffers from a number of limitations which have to be taken into account by the analyst when using it. The most obvious relates to the arbitrariness of the CV threshold of to 2. In our specific application, this threshold seems to effectively separate attribute attendance and non-attendance, but this will not always necessarily be the case. In this sense, we show that the quantiles and the kernel density plots of the CV of each attribute provide useful information, indicating the suitability of this approach (or the lack of it) regarding the threshold of 2 for successfully capturing ANA behavior. Taking this information into account, the analyst may decide whether this or another threshold would be more suitable to identify ANA behavior for each attribute. Furthermore, it is worth noting that the reliance of this approach on the CV to distinguish such behavior entails the risk of confounding effects, which could be related to the experimental design or certain types of respondent behavior, such as variety-seeking[12]. Particularly, when the CE relies on a reduced number of choices, respondents' trade-offs may not provide enough information to significantly reduce the standard deviation of random parameters. This may be especially relevant when employing orthogonal designs which are not predicated on prior assumptions on random parameter distributions. In this regard, the analyst can conduct an ex-post test to check for any unintended effects relating to the former (for example, using regression analysis, as shown in our study) and –partially– the latter (by looking at the parameter estimations). In addition, it would be advisable to use specific questions to control for these potential confounding behaviors.

The specialized literature shows a complementary stream of ANA behavior modeling based on finite mixing, especially relating to the so-called equality constrained latent class (ECLC) models (Scarpa et al 2009, Campbell et al 2011, Scarpa et al 2013). Using this approach, researchers can analyze different heuristics by constraining the attributes entering the utility function, which is very convenient

[12] In our study, however, we do not believe that there have been important confounding effects between ANA and variety-seeking behaviors, as the high CVs encountered for ANA respondents are mostly determined by very low conditional means (the inferred utility function for the non-attenders lacks random taste heterogeneity and significant taste parameters).

given the variety of choice patterns elicited from ANA −as is shown in our application. However, as for the HHA, this approach is not free of limitations. For example, there is a degree of arbitrariness in the selection of the different non-attendance profiles to be analyzed through the constraint classes, and this clearly entails trade-offs between the number of classes and the feasibility of modeling. In addition, there is also a notable risk of confounding effects between non-attendance and taste heterogeneity (Hess et al 2012) since respondents with weak preferences for an attribute would be incorrectly classified as non-attenders (Hole et al 2016). A further application of ECLC to the context of supply-side environmental valuation would undoubtedly contribute to this discussion. Additionally, both for HHA and ECLC, it would be useful to incorporate recent advances aimed at disentangling ANA behavior, such as addressing sequential and individual scale heteroscedasticity (Scarpa et al 2010, Balcombe et al 2015), jointly analyzing importance ranking and non-attendance data (Chalak et al 2016) and adopting an endogenous ANA approach (Hole et al 2016, Hole et al 2013, Hole 2011, Collins 2012), as well as accounting for potential correlation between scale and preference heterogeneity (Thiene et al 2015), among others.

While 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. This would suggest that the failure to address ANA in these types of studies may not have produced the large impacts on welfare estimates often reported for demand-side WTP contexts (Hensher et al 2005, Scarpa et al 2009, Hole 2011, Hess et al 2012, Kragt 2013, Collins et al 2013, Scarpa et al 2013), although some studies do not report any such impacts (e.g., Hole et al 2013). The higher level of attendance to the monetary attribute reported in our WTA context compared to the levels reported for WTP contexts is very likely linked to these different impacts on welfare estimates. 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 behavior.

We also provide some insights into the explanations for ANA behavior by jointly modeling 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 behavior 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 (Uthes and Matzdorf 2013, Siebert et al 2006). Overall, our results point to 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. This shows the important role played not only by attribute non-attendance but also by attribute-level non-attendance in these valuation contexts.

With respect to the different individuals' status quo level –and its obvious impact on welfare estimates–, it is worth noting that this is something rarely reported in demand-side environmental valuation studies (see, for example, Marsh et al 2011). Conversely, although a consideration of the different individuals' status quo is, in theory, relevant in studies analyzing ES providers' WTA, we find that it is not yet sufficiently acknowledged (to our knowledge, few studies highlight this, including Vedel et al 2015, Villanueva et al 2017b), 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 studies and including it in the analysis.

The analysis of predictors of ANA behavior offers some interesting interpretations related to the reasons for non-attendance. Thus, in line with the findings of Caputo et al (2013), Balcombe et al (2015) and Hole et al (2016), most of these predictors, especially those related to the farmers' status quo and perceptions about the advantages of the AES and, to a lesser extent, farm characteristics and management, suggest different patterns of preference heterogeneity likely due to genuine indifference (i.e., not placing value on certain attributes). However, only a few factors seem to be more closely related to simplified decision heuristics. Specifically, these include respondents' educational level, training, and age. Consequently, the analysis of factors behind ANA behavior has helped shed light on the extent to which farmers' behavior correspond to ANA as a special form of preference heterogeneity. To some degree, this finding is in line with that of Hole (2016), since when non-attendance is interpreted as a form of preference heterogeneity, approaches accounting for ANA yield similar inferences to those from standard models. Nonetheless, it is worth recognizing that a combination of both behavioral patterns (genuine indifference and simplified decision heuristics) may be an even more plausible alternative.

CONCLUSIONS

Whereas discontinuous preferences have been systematically investigated in demand-side environmental valuation assessments, there are virtually no studies that explore this topic in analyses focusing on the supply side. This is in spite of the growing body of literature analyzing ecosystem service providers' preferences towards incentive-based schemes (e.g., PES and AES). To the best of our knowledge, our study joins that of Espinosa-Goded and Barreiro-Hurlé (2010) in representing the only two studies to account for ANA behavior in an analysis of ecosystem service providers' WTA. Additionally, among the novelties of our study, it is worth highlighting that it is the first of this type to compare stated and inferred ANA approaches (using Hess and Hensher (2010) proposal for the latter), their concordance and resulting WTA estimates, and to explore determinants of ANA for both approaches.

The results provide evidence of ANA behavior in respondents' choices, with few respondents attending to all the attributes. By accounting for ANA, using either the stated or inferred approach, model fits are improved compared to the uncorrected model, suggesting that both approaches successfully capture the different behavioral patterns of the two groups of respondents (those who attend to the attributes and those who ignore them). We have no conclusive results on the extent to which the inferred approach is better than the stated one, although the former seems better able to detect such behavior. WTA estimates show little to no significant differences between the models accounting for ANA and the uncorrected model, suggesting that the failure to address ANA in these types of studies may not produce the large impacts on welfare estimates reported for other valuation contexts. This can partially be explained by the low level of non-attendance to the monetary attribute encountered for both stated and inferred ANA. It is plausible that the different valuation context, with farmers deciding whether or not to change their business management by adopting certain environmentally-friendly practices (usually involving opportunity costs) depending on the compensation offered, is behind this.

We also provide insights into the explanations for ANA behavior by jointly modeling stated and inferred ANA using bivariate probit models. Our results show a wide variety of variables influencing non-attendance to attributes, including individual status quo, respondents' characteristics and attitudes, perceptions and knowledge, as well as farm characteristics and management. 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 largely comply with the scheme requirements. This implies that not only attribute non-attendance but also attribute-level non-attendance plays an important role in these valuation contexts. Nevertheless, further research is clearly needed to establish a common framework for dealing with ANA behavior, to understand its impact on welfare estimates in different contexts, and to recognize what factors lie behind it.

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APPENDIX A

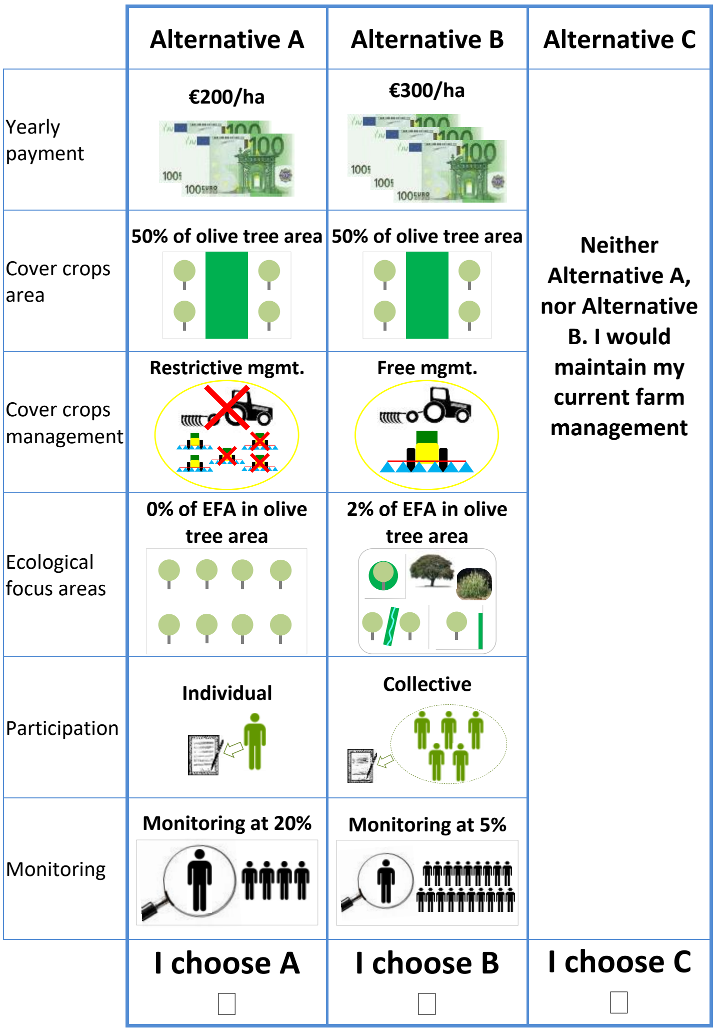

Fig. A.1. Example of a choice set.

APPENDIX B

Table B.1. Attribute specific quantiles of the coefficient of variation of the conditional parameters

Quantile	CCAR	CCMA	EFA	COLLE	PAYM
0.10	0.33	0.33	0.39	0.35	0.29
0.25	0.49	0.46	0.56	0.53	0.36
0.50	0.85	0.77	0.86	0.81	0.48
0.75	1.56	1.48	1.81	1.83	0.68
0.90	2.88	3.18	4.75	3.84	1.22