Economic Analysis and Policy 71 (2021) 211–226

Contents lists available at ScienceDirect

Economic Analysis and Policy

journal homepage: www.elsevier.com/locate/eap

Modelling economic policy issues

A straightforward diagnostic tool to identify attribute non-attendance in discrete choice experiments

María Espinosa-Goded [a,b,*], Macario Rodriguez-Entrena [c], Melania Salazar-Ordóñez [c]

[a] European Commission, Joint Research Centre and Universidad de Sevilla, Spain
[b] Faculty of Economics and Business/Department of Economic Analysis and Political Economy, Universidad de Sevilla, Avda. Ramón y Cajal 1, 41.005 Sevilla, Spain
[c] WEARE-Water, Environmental, and Agricultural Resources Economics Research Group, Universidad de Córdoba, Puerta Nueva s/n, E-14002 Córdoba, Spain

ARTICLE INFO

Article history:
Received 15 September 2020
Received in revised form 19 April 2021
Accepted 19 April 2021
Available online 28 April 2021

JEL classification:
C18
C25
Q51

Keywords:
Attribute non-attendance (ANA)
Inferred ANA
Piecewise regression
Coefficient of variation
Willingness to pay (WTP)

ABSTRACT

To distinguish between respondents that have attended to/ignored an attribute in discrete choice experiments (DCE), Hess and Hensher (HH) apply the coefficient of variation of the conditional distribution, setting a threshold of 2 as a conservative rule of thumb. This paper develops an analytical framework (piecewise regression analysis — PWRA) to refine the HH approach, offering a flexible method to identify attribute non-attendance (ANA) in highly context-dependent DCE. It is empirically tested on a dataset used to value agricultural public goods. The results suggest that the identification of non-attendance and goodness of fit of different random parameter logit models that accommodate ANA are better when the framework developed in this research is applied. When comparing welfare estimates from the HH and PWRA approach, significant differences are observed. Consequently, the flexibility of the PWRA notably contributes to revealing context-specific ANA patterns that can help to provide more accurate welfare measures and therefore policy recommendations.

1. Introduction

Discrete Choice Experiments (DCE) are one of the most commonly-used methods in the stated preference literature. They have been applied in a wide variety of economic fields, to examine matters such as health care (e.g. De Bekker-Grob et al., 2012), consumer behaviour (e.g. Scarpa et al., 2005), agri-environmental policies (e.g. Villanueva et al., 2017 and Espinosa-Goded et al., 2010) or transport (e.g. Hensher and Truong, 1985). Applications of DCE are supposed to fulfil a number of underlying axioms, especially the axiom of continuity. This axiom, which is a core principle of the DCE, is based on the standard neoclassical model of consumer choice. It assumes unlimited substitutability among attributes, such that decision-makers uniformly consider all available information before making trade-offs among the attributes used to describe alternatives (Puckett and Hensher, 2009). However, passive bounded rationality is behind the findings of many studies (e.g. Hensher et al., 2005; Alemu et al., 2013; Rodríguez-Entrena et al., 2019), revealing that individuals do not consider (and therefore do not trade off) all the attributes, a behaviour encompassing discontinuous preferences or

* Corresponding author at: European Commission, Joint Research Centre and Universidad de Sevilla, Spain.
E-mail address: megoded@us.es (M. Espinosa-Goded).

https://doi.org/10.1016/j.eap.2021.04.012

attribute non-attendance (ANA). Not attending to some attributes is considered a non-compensatory attribute processing strategy as no amount of the ignored attribute will compensate for the attributes that are attended to (Campbell et al., 2008).

Ignoring these deviations from the theoretical fully-compensatory behaviour could result in a biased estimation of the respondent utility function (e.g. Carlsson et al., 2010; Kragt, 2013; Kravchenko, 2014). Thus, welfare measures in willingness to pay (WTP) and willingness to accept (WTA) contexts can result in biased estimates (Colombo and Glenk, 2013; Rodríguez-Entrena et al., 2019) if, for example, the marginal utility of the monetary attribute is lowered/inflated due to respondent's non-attendance behaviour. As a case in point, Rodríguez-Entrena et al. (2019) reveal the strikingly low level of non-attendance to the monetary attribute in a supply-side WTA assessment (dealing with the provision of ecosystem services) in comparison to demand-side WTP environmental valuation studies, which report much higher levels. For example, Campbell et al. (2011), Scarpa et al. (2009) and Kragt (2013) report levels of non-attendance to the monetary attribute of 90%, 61%, and 39% respectively, producing notable differences in WTP estimates when accounting for the ANA.

In an attempt to address this issue, ANA is usually factored into DCE models, yielding significant improvements in model fit and more precise parameter estimates (Leong and Hensher, 2012). A review of the ways used to deal with ANA can be found in Lew and Whitehead (2020). One of the simplest modelling approaches is to consider self-reported ANA information; however, this may be subject to reporting error since there is no one-to-one correspondence between stated and actual (i.e., revealed) processing strategies in the use of respondents' statements assessing ANA (e.g. Hess and Hensher, 2010; Scarpa et al., 2013; Hess and Hensher, 2013; Ortega and Ward, 2016). Hole et al. (2013) find evidence that stated ANA can be a useful indicator of the prevalence of non-attendance in the data. However, Hess and Hensher (2013) in a hybrid stated ANA model[1] show that respondents who indicate that they do not attend to a given attribute in reality simply assign it lower importance: thus, the higher the probability of indicating that they ignore a given attribute, the lower the perceived importance of that attribute. In the same vein, the study by Chalak et al. (2016) represents the first attempt to jointly investigate stated ANA and importance ranking measures of the attributes by employing a generalisation of a mixed logit approach. The results indicate that neither ANA nor ranking data should be seen as clearly superior, and that stated non-attendance is not consistent with zero marginal utility. Hensher et al. (2013) estimate combinations of different latent class models (fixed, random, and incorporating attribute processing strategies), finding that the random parameter specifications increase the share of respondents in the full attendance class, compared to the fixed specification. This indicates that some respondents assign a low marginal utility rather than a zero marginal utility, which corresponds to the class incorporating ANA.

The context-dependent uncertainty surrounding respondents' self-reported ANA information is why current research on discontinuous preferences has largely shifted to inferring the actual processing strategies from observed or experimental behaviour (Hess and Hensher, 2013). Inferred ANA reveals behaviours from the experimental data through the use of diverse econometric approaches (e.g. Campbell et al., 2011; Caputo et al., 2013; Colombo et al., 2016; Hole et al., 2013; Scarpa et al., 2009). Among such studies, Hess and Hensher (2010) propose a methodological approach (HH approach) to infer non-attendance behaviour based on ex-post modelling. These authors apply a random coefficients formulation of the mixed multinomial logit model in order to analyse the respondents' variations in the coefficient estimates, inferring the ANA behaviour from observed choices. The coefficient of variation (CV) is applied to identify respondents that have attended to/ignored each attribute, with it being interpreted as the noise-to-signal ratio. If this ratio is high, the respondent-specific normal distribution is over-spread, indicating the respondent has not paid much attention to the attribute (see, for example, Scarpa et al., 2013). In this respect, Hess and Hensher (2010) suggest a threshold value of 2 to distinguish between respondents who attend to/ignore an attribute, conceding that this is a rather arbitrary albeit conservative threshold, and that further research is required to define a less arbitrary threshold.

Therefore, the aim of this paper is to deploy a straightforward analytical framework based on the HH approach, thereby offering a flexible diagnostic tool to identify ANA in highly context-dependent DCE. The approach developed in this research allows the researcher to analytically determine the thresholds of the CV to identify ANA patterns. In order to do so, a piecewise regression analysis (PWRA) is applied to the individual parameter estimates derived from a random parameter logit model (RPLM), a widely-used specification in DCE. To the best of our knowledge, this is the first attempt to develop a highly-customisable methodological framework to estimate attribute-specific CV thresholds, rather than relying on arbitrary values; indeed, this feature is one of the main contributions to the existing literature. Another key contribution of this paper is that it provides a straightforward diagnostic tool to assess the importance of ANA in the applied economics community, when the main aim is not methodological research. The proposed methodological approach is empirically tested on a DCE dataset from an assessment of agricultural public goods. The analysis first compares the rates of inferred ANA in the HH and PWRA method, before assessing the goodness of fit and the welfare measures of both methods.

[1] The hybrid stated choice models (Hess and Hensher, 2013; Chalak et al., 2016; Bello and Abdulai, 2016) solve the endogeneity bias stemming from the correlation between the stated ANA and the error terms.

2. Literature review

The development of alternative strategies to account for ANA in DCE has attracted a good deal of attention in the last decade. Indeed, the literature contains different attempts (e.g. Campbell et al., 2008; Colombo and Glenk, 2013; Hensher et al., 2005; Campbell et al., 2011; Caputo et al., 2013; Colombo et al., 2016; Hole et al., 2013; Scarpa et al., 2009) to find the best way of mitigating the impact of ANA on welfare estimates via non-compensatory decision schemes (such as simplified decision rules and heuristics). Among the main methodological approaches to address these inconsistencies in the theoretical fully compensatory behaviour as utility maximisers (which can be interpreted as non-compensatory behaviour), the equality constrained latent class (ECLC) modelling (Scarpa et al., 2009) and the abovementioned HH approach (Hess and Hensher, 2010) are particularly notable.

The ECLC modelling approach (e.g. Scarpa et al., 2009; Campbell et al., 2011) has been widely used since it enables the analysis of different heuristics to identify different ANA patterns by constraining to zero the class attribute coefficients entering the utility function. However, this model is not free from drawbacks. First, it requires an iterative process, which has to be defined in advance by restrictions on parameters. Likewise, the existence of numerous attributes and levels can prevent the mapping of all potential ANA patterns (Hole, 2011; Hole et al., 2013) since it entails a trade-off between the number of classes and the feasibility of modelling. In addition, Hess et al. (2013) argue that the latent class approach might be misguided as the results could be confounded by regular taste heterogeneity, i.e. respondents with weak preferences for an attribute would be incorrectly classified as non-attenders. In this vein, a more flexible option was designed by Hess et al. (2013) and Hensher et al. (2012) who propose the addition of random parameters to the latent structure in order to simultaneously capture preference heterogeneity in the distributions and ANA patterns through the coefficients constrained to zero. Hess et al. (2013) assume independent ANA patterns, which may be too strong of an assumption in some contexts. In the case of Hensher et al. (2012), correlated ANA patterns are assumed at the cost of a loss of parsimony due to the high complexity in the number of parameters to be estimated.

In the same line of research, Campbell et al. (2011) extend the latent class analysis to accommodate the idea that each latent class may be comprised of subsets of respondents who, while having the same preferences in terms of part-worth utilities, differ in their level of scale variance (uncertainty). They provide evidence of the crucial role played by ANA processing strategies, finding substantially lower WTP compared to an "all-attributes-are-relevant" processing paradigm. Alternatively, Collins et al. (2013) suggest the use of a generalised random parameters model that allows for an arbitrary degree of correlation of non-attendance across attributes. In this model, covariates can be entered into the ANA class assignment component of the latent class model, allowing the ANA rate to vary across respondents. Results reported by the abovementioned authors show that using stated ANA as a covariate led to an improvement of model fit. Thiene et al. (2015) develop a flexible modelling approach through an advanced latent class specification that addresses the unobserved heterogeneity of error scale by simultaneously estimating interpersonal variation in scale and taste, while accounting for ANA. This approach is noteworthy in that the modelling does not assume that all individuals respond to the choice experiment with the same consistency, indicating that error variances are not constant within or between individuals. It could thus prevent a potential confounding effect between utility parameters and the unobserved distribution of error variances, which could be critical for an accurate assessment of ANA. In health economics, an alternative approach related to the ECLC approach is developed by Hole (2011, p. 203), who proposes an "endogenous attribute attendance (EAA) model with a two-stage structure where in the first one the decision-maker chooses the subset of attributes to take into account when choosing an alternative; and in the second the preferred alternative is chosen conditional on the choice of attributes in stage one". The EAA model outperforms a standard logit model in terms of goodness of fit and produces substantially different estimates of WTP. For comparative purposes, Hole et al. (2016) employ an ECLC model and a variant of the EAA model, demonstrating the benefit, in terms of model fit, of explicitly modelling attribute attendance. They find that when non-attendance is interpreted as a form of preference heterogeneity, the inferences from the ECLC and EAA approaches are similar to those from standard models. Conversely, if it is assumed to be a strategy of simplifying the choice, then the results differ from a standard approach. Interestingly, the abovementioned authors call for further exploration of the reasons for non-attendance to assess how this behaviour is modulated by the two sources of non-attendance — not placing a value on an attribute and simplifying decision heuristics.

Regarding the HH approach as a strategy for dealing with the abovementioned inconsistent behaviour, Mariel et al. (2013), who began this line of research, examine the validity of the proposed CV threshold value of 2. In their study, different values in the range of 0.5 and 3.5 are tested in a simulation approach in order to assess the levels of ANA. They conclude that the threshold value in the HH approach seems to be very conservative since it may be valid only for low levels of ANA. Collins et al. (2013) additionally optimise the thresholds by forcing the aggregate inferred ANA rate to equal the stated ANA one. They thus confirm the conservative nature of the threshold, which leads to very low inferred ANA rates. Results show that while the optimisation increases the inferred ANA rate, it also leads to a fair degree of misclassification. In addition, Scarpa et al. (2013) find that the frequencies of ANA estimated using the HH approach – applying the CV threshold value of 2 – do not follow a regular pattern when compared with those from SA and ECLC models. They thus conclude that there is no clear winner between those two methods when it comes to inferring the stated non-attendance and discovering the true ANA patterns.

3. Implementing a new method to estimate the ANA threshold value

3.1. The random parameter logit model

The method used to identify ANA was divided into three steps. In step one, a basic RPLM was estimated and the associated conditional mean and variance for each respondent were recovered. In step two, a PWRA was used to split respondents into layers of attenders and non-attenders based on the parameters estimated in step one. In step three, to accommodate the ANA, a new random parameter ANA model (RPANA) was estimated, conditioned on the results from step two.

Regarding step one, the RPLM formulation has fast become one of the most widely-used econometric structures for the analysis of DCE since it allows parameters to vary across respondents, flexible substitution patterns and correlation with unobserved factors (Train, 2003). In this study, the model was extended by introducing heterogeneity in means through interactions with socio-demographic profiles to provide a more behaviourally meaningful location of the individuals on the parameter distribution.

In this model, the utility function associated with each of the alternatives j for respondent n is specified as:

$$U_{nj} = ASC_{SQ} + \beta_n' X_{nj} + \gamma_n' Z_n X_{nj} + \varepsilon_{nj} \tag{1}$$

where $\mathrm{ASC_{SQ}}$ is the alternative specific constant for the status quo choice, X_{nj} is a vector representing the k attributes presented to individual n in each alternative , Z_n represents the socio-demographic profile, β_n' reflects individual preferences for each attribute k and γ_n' captures systematic preference heterogeneity. The error terms, ε_{nj}, follow a Gumbel distribution and are assumed to be constant among the different choices made by an individual (the data has a panel structure). The β coefficients are randomly distributed in the population following a density function $f(\beta|\theta)$, where θ is a vector of parameters characterising the density function that captures individual deviations from the mean. In this study, we assumed that all attribute parameters follow normal distributions. The choice of the normal distribution was driven by the need to compare the HH threshold value (normal distribution with CV ratios higher than 2 is assumed to be over-spread) with our approach. This decision was based on the need for flexibility in the parameter estimates in order to implement the PWRA diagnostic tool, since the core aim was the estimation of the threshold values to identify ANA and not the estimation of WTP values.

In this behavioural model, the individuals' choices reveal something about their tastes, which can be assessed after estimation. Therefore, two distributions can be obtained: the distribution of tastes in the population $f(\beta|\theta)$ (described before and usually labelled as an "unconditional" distribution) and the distribution of tastes in the subpopulation of respondents that make particular choices $g(\beta|\theta)$ labelled as a "conditional" distribution of the observed choices made by specific respondents.

Following Train (2003), we assumed that $y_n = \langle y_{n1}, \ldots, y_{nT} \rangle$ is the respondent's sequence of chosen alternatives, with T being the number of choice situations. The variable X_{nj} is represented collectively for all alternatives as X_n. The probability of the respondent's sequences of choices is the integral of $P(Y_n|X_n, \theta)$ over the distribution of β:

$$P(Y_n|X_n, \theta) = \int P(Y_n|X_n, \theta) f(\beta|\theta) d\beta \tag{2}$$

The distribution of the subpopulation $g(\beta|\theta)$ corresponding to the conditional estimates can be derived using Bayes' rule:

$$g(\beta|Y_n, X_n, \theta) = \frac{P(Y_n|X_n, \beta) f(\beta|\theta)}{P(Y_n|X_n, \theta)} \tag{3}$$

Since all the elements on the right-hand side are known, the conditional distribution of β for each respondent can be estimated. The estimated conditional mean and variance for each respondent (n) and attribute k is given by $\beta_{\mathrm{kn}} \sim \mathrm{N}(\mu_{\mathrm{kn}}, \sigma^2_{\mathrm{kn}})$. We assumed no correlation among parameters in order to replicate the methodological approach proposed by Hess and Hensher (2010), thereby enabling the comparison between the two procedures under the same conditions. In the research by Collins et al. (2013), it is shown that the correlation structure in RPANA models might be important; however, as the focus of this research was the estimation of the threshold values, the most common model specification was applied.[2] In addition, the choices were modelled applying a panel structure where all random error terms (ε) follow a Gumbel distribution and were assumed to be constant among the different choices made by each individual.

The RPLM was used in step one to define the individual conditional parameters for the estimation of the PWRA (step two), in order to determine the threshold value used to distinguish between attenders and non-attenders. The RPANA approach was used in step three to accommodate the ANA in its structure. ANA is identified using the inferred HH and PWRA approaches. Here, the utility function was decomposed into two layers to simultaneously estimate specific parameters for the attender and non-attender classes. This approach is an efficient way to model attribute processing strategies (Hess and Hensher, 2010), compared to restricting the attributes of the non-attendance layer to zero (Kragt, 2013) or exploring the heterogeneity around the mean parameters (Espinosa-Goded and Barreiro-Hurlé, 2010).

2 In any case, the procedure depicted here is also fully applicable to RPLM with correlated attributes.

3.2. Welfare measures

The marginal rates of substitution between the PGaE attributes (non-monetary) and the negative value of the monetary attribute were used to calculate the WTP estimates ($WTP_{PgaE} = \beta_{PgaE}/\text{-}\beta_{TAX}$) and being able to compare both inferred approaches (HH and PWRA).

The monetary attribute was not statistically significant in the non-attendance layer in the HH and PWRA approaches; accordingly, the WTP vectors were estimated considering only the utility layer in which the monetary attribute was traded-off and significantly different from zero. Thus, when estimating the welfare measures, the group of respondents not considering the monetary attribute were deemed to be an inconsistency[3] from an economic theory perspective (Hensher et al., 2012; Hess et al., 2013). Therefore, following the approach of Hensher et al. (2012) and Hess et al. (2013), the WTP values of the utility function with a significant monetary attribute were applied to the entire population.

The widely-used parametric bootstrapping approach proposed by Krinsky and Robb (1986) was used to calculate the mean and the confidence interval of the WTP estimates. Under this approach, the uncertainty (standard errors) attached to the structural parameters of the distributions are considered to take the simulated draws required. The complete combinatorial test proposed by Poe et al. (2005) was used to assess whether there are significant differences among the WTP estimates for the alternative approaches.[4]

3.3. The new way of estimating the coefficient of variation threshold

Hess and Hensher (2010) put forward the idea of using the CV (expressed as $CV_{kn} = \sigma_{kn}/\mu_{kn}$) of the RPLM conditional parameter estimates to distinguish between respondents attending to/ignoring an attribute. The authors apply the CV as a measure that identifies when the conditional mean is indistinguishable from zero. Thus, to better reflect the actual behaviour incorporating uncertainty, the CV is employed instead of working directly with the mean of the conditional distributions. Hess and Hensher (2010) suggest the value of 2 as the breakpoint between attendance and non-attendance, stating that it is somewhat arbitrary, but conservative.[5] They encourage the research community to find a way of customising the breakpoints, acknowledging that "more work is required to evaluate the impact of the threshold choice on results" (Hess and Hensher, 2010, p. 786). Following that recommendation, in this research, a methodological framework was developed to analytically determine the threshold value of the CV to allocate respondents to the attending to/ignoring classes. To that end, the main assumption was that the function which relates the parameter coefficient estimates (μ_{kn}) with the CV (cv_{kn}) behaves differently for respondents who attend to/ignore the attribute. Therefore, we used a piecewise linear regression (also called threshold or segmented regression) that allows multiple linear models to be fitted to the dependent variable (the CV) for different ranges of the independent variable (μ_{kn}). Hence, it was assumed that μ_{kn} predicts cv_{kn} differently over certain ranges of μ_{kn}. In such instances, if two adjoined lines are estimated, the breakpoint of the regression system represents the threshold value where the slope of the linear function changes significantly. The value of the breakpoint is not known and must be estimated. In our estimation, there was only one breakpoint at $x = c$ since the PWRA is used to differentiate between the two groups of respondents.

Thus, the model was written as follows:

$$\begin{aligned} y &= a_1 + b_1 x \quad \textit{for } x \leq c \\ y &= a_2 + b_2 x \quad \textit{for } x > c \end{aligned} \tag{4}$$

where $y = cv_{kn}$; $x = \mu_{kn}$; and $c =$ breakpoint.

In order for the regression function to be continuous at the breakpoint, the two equations for y need to be equal at the breakpoint (when $x = c$):

$$\begin{aligned} a_1 + b_1 c &= a_2 + b_2 c \\ a_2 &= a_1 + c(b_1 - b_2) \end{aligned} \tag{5}$$

Then by replacing a_2 with the equation above, the result is a piecewise regression model that is continuous at $x = c$:

$$\begin{aligned} y &= a_1 + b_1 x & \textit{for } x \leq c \\ y &= a_1 + c(b_1 - b_2) + b_2 x & \textit{for } x > c \end{aligned} \tag{6}$$

This nonlinear least square regression approach was estimated using the PROC NLIN routine in SAS Enterprise guide version 5.1. The estimation was conducted using the Marquardt method (Moré, 1978) (also known as damped least-squares), a method based on an iterative procedure applied to solve non-linear least squares problems. The user has to provide an initial value of the parameter vectors (a_1, b_1, b_2 and c) and then the best breakpoint is selected based on the minimum mean square error. These initial values needed to start the iteration procedure are estimated by applying a non-parametric smooth regression to the data. In particular the LOESS procedure in SAS (SAS Institute Inc., 2015) (a weighted

[3] While it is also plausible that the levels of the monetary attribute are not relevant for some respondents, it would represent a stated preference artefact rather than real life behaviour.

[4] The complete combinatorial approach involves calculating all the differences of the elements in two distributions and assessing the value of the resulting cumulative distribution of the vector of differences to check for a statistical difference between them.

[5] The interested reader can refer to the original paper for a complete description of the methodology.

least squares procedure) is used to fit linear or quadratic functions of the predictors at the centre of neighbourhoods. Based on a graphical interpretation, we considered the initial breakpoint and estimated a simple linear regression model[6] above and below the breakpoint, which was incorporated in the iteration procedure to fit the PWRA model. Therefore, in this modelling exercise, the breakpoint reflected the value of the attribute coefficient estimates that distinguished between respondents attending to/ignoring the attribute.

4. Case study

To test the new approach, the method was applied to a case study rooted in an empirically-based framework to value Public Goods and Externalities (PGaE) of European Union (EU) agriculture (Madureira et al., 2013). The questionnaire for this large-scale EU survey was designed and implemented to evaluate farmland abandonment in the Mediterranean uplands. In these dry, hilly areas, a dramatic increase in the abandonment of agricultural activity is expected if the relevant policies are not implemented. In this case, the public-good policy would seek to prevent the expected negative effects of this trend on the relevant PGaE. The PGaE in the agricultural uplands evaluated in the research by Madureira et al. (2013) are landscape, farmland biodiversity, fire risk and soil erosion. The questionnaire was administered in Portugal and Germany, allowing the researchers to evaluate both the resident and non-resident preferences, respectively, towards the provision of the abovementioned public goods by agricultural Mediterranean uplands, which entails altruistic benefits in the sense of the increasing utility from giving (Andreoni, 1990). First, the questionnaire was tested by means of a pre-test survey of 30 people. Finally, 900 completed questionnaires were obtained from three sub-samples (300 for each sub-sample): (1) Portuguese residents in Lisbon conurbation area with CAPI (Computer-Assisted Personal Interviewing) face-to-face survey (FTF_PT); (2) Portuguese, national sample, with CAWI (Computer-Assisted Web Interviewing) panel-based (WEB_PT); (3) German, national sample, with CAWI panel-based (WEB_DE). Protest responses were identified as those that choose the status quo in all the choice tasks (serial non-participating). In total, 26, 18 and 36 respondents were identified in FTF_PT, WEB_PT and WEB_DE, respectively. These respondents were eliminated from the analysis, however, as highlighted by Barrio and Loureiro (2013), they may be true zero respondents. A limitation of this analysis was that it did not include of a follow-up question to clarify this aspect (Villanueva et al., 2017). The socio-demographic characteristics of each sub-sample are presented in Appendix A. Significant differences (t-test corrected by a Bonferroni adjustment to account for multiple comparisons) were observed in the socio-demographic variables (10 out of the 12 variables) among the three sub-samples (FTF_PT, WEB_PT and WEB_DE). The alternative options were built by means of attributes which represented the public goods provided by agricultural Mediterranean uplands described in Table 1.

The levels of the environmental attributes were set as the percentage of the area that benefited from the public good programme. Hence, people could choose to prevent the reduction in the current level of provision of each PGaE in the entire area or only in 50% of it, or choose the policy-off scenario, in which the area that benefited was set to 0%. The cost attribute was specified as an overall increase in individual income tax for a period of five years. This time period was chosen to match the duration of the Common Agricultural Policy (CAP) Agri-Environmental Scheme payments to farmers, ensured by five-year contracts (European Commission, 2019a). The levels for the cost attribute were first established using an estimate of the average amount EU taxpayers currently pay to fund the CAP as a guideline, currently around 40 euro per household. This figure was estimated considering a CAP expenditure of around 50 billion euro in 2010 (European Commission, 2019b) and an EU27 population of 500 million. This worked out at around 100 euro per capita for the overall CAP expenditure. To translate this into a per household expenditure, the authors took an average household for the planned survey of just over two individuals per household. The resulting amount was set as the maximum bid in the survey.

Experimental design techniques were applied because the combination of the attributes with their respective levels gave rise to 256 possible choice alternatives and 4,096 possible choice sets. A D-efficient design (Hensher et al., 2015; Rose and Bliemer, 2009) was constructed with the Ngene software (version 1.1.1). A multinomial logit model specification was assumed, with values close to zero as priors of the PGaE coefficient estimates, given that the literature review on the valuation of multiple public goods did not provide any indicative values. The final experimental design comprised 20 choice sets, which were randomly assigned to 4 blocks of 5 choice sets (Madureira et al., 2013).

[6] The main aim is simply to retrieve unbiased estimates in order to pinpoint the breakpoints interpreted as the transition from attendance to non-attendance. If the piece-wise regression was to be used any further, the traditional linear regression assumptions should be checked. Here, the nonlinear approach ensures correctness but even if the linear regression assumptions were violated, the breakpoint estimates would still be valid. Violations of the normality and/or homogeneous variance assumptions result in unreliable estimates of the standard error and confidence intervals, but the parameter estimates themselves are unbiased (Neter et al., 1990). Likewise, regression analysis is generally considered robust to violations of normality when the sample size exceeds 200 observations (Hair et al., 2019). Thus, while the PWRA clearly serves our main objective of determining a customisable procedure to locate the breakpoints, it should be noted that it is just the instrument used to find the breakpoint and is not used to make predictions derived from the estimations.

Table 1
PGaE and price attributes.
Source: Madureira et al. (2013)

Attributes	Commitments for farmers	Benefit to society	Levels (of the area that benefits from the public good programme)
Soil erosion (ERO) 	Maintaining terraces in high slopes. Keeping the soil covered with vegetation and avoiding soil ploughing.	Ensure soil fertility. Ensure the soil's ability to support landscape and biodiversity.	0%; 50%; 100%.
Biodiversity (BIOD)  	Conserving the habitats of threatened animal and plant species. Adopting an environmentally friendly farming style.	Preserve animal and plant species from extinction. Enjoy nature for recreation and leisure.	0%; 50%; 100%.
Resilience to fire (FIRE) 	Cleaning scrub growth. Keeping the farmed elements in the landscape mosaic to create barriers to fire progression.	Ensuring the safety of people and goods. Prevent air pollution and greenhouse gas emissions.	0%; 50%; 100%.
Landscape (LAND) 	Keeping the traditional crops in production. Adopting an environmentally friendly farming style.	Safeguard the cultural heritage. Enjoy high quality and tasty products. Enjoy the traditional countryside for recreation and leisure.	0%; 50%; 100%.
Price (TAX) 	Annual cost per household for a period of 5 years.		3; 12; 21; 39 €/year

5. Results

5.1. Threshold value estimation: Piecewise regression results

As explained in Section 3, the conditional distributions of the RPLM considering heterogeneity in the means (see Appendix B) were used in the PWRA to estimate the threshold breakpoints. The parameter estimates and the significance of the regression are shown in Appendix C. The F-test in all the cases rejected the null hypothesis that the breakpoint did not provide a significant extra contribution to the success of the simple linear regression. As an example, the PWRA for the BIO attribute in the Portuguese sample (FTF_PT) is graphed in Fig. 1.[7] As in the case of Hess and Hensher (2010), a high CV was obtained only for respondents that had a very low conditional mean (virtually zero).

Table 2 shows the threshold values of the CVs (in terms of notation, the breakpoints are the values expressed on the *x*-axis, reflecting the coefficient estimates, while the threshold values are the correspondence of the breakpoints on the *y*-axis, reflecting the CV values distinguishing between attenders/non-attenders). The range of the threshold values varies between 0.5 (FIRE attribute in the FTF_PT) and 5.13 (TAX attribute in the WEB_DE). The thresholds are highly sample- and attribute-specific; as such, standardising the ANA based on a fixed value would not reflect this heterogeneity and, therefore, there would be a non-negligible risk of not measuring the real attribute processing strategies. This heterogeneity is reflected in the sensitivity analysis in Table 12 in the Appendix D where it is reflected the threshold values for different percentiles of respondents attending to/ignoring each attribute. As an example, for the FTF_PT survey the threshold value of the CVs to have 90% of respondents in the attendant layer (10% in the non-attendant layer) was 2.43, 2.08, 0.55, 0.62 and 5.08 for ERO, BIO, FIRE, LAND and TAX respectively.

Overall, it can be concluded that the threshold values estimated with the PWRA were lower than the HH value of 2 for the PGaE attributes, but higher than 2 for the key attribute, TAX (cost). Consequently, the rate of non-attenders was

[7] For ease of reading, only this example is displayed. All the plots are available from the authors on request.

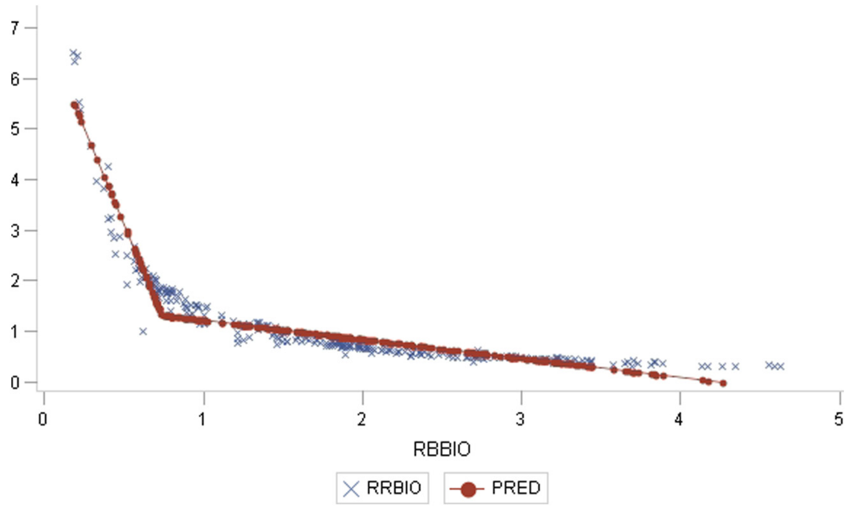

Fig. 1. PWRA from the RPLM estimations for the attribute BIO in the FTF_PT survey. Note: The *x*-axis represents the conditional parameter estimates (μ_{kn} = *RBBIO*). The *y*-axis shows the conditional CV estimates (cv_{kn} = *RRBIO*) and the PWRA prediction (PRED).

Table 2
Threshold value (TV) estimates and percentage of respondents ignoring the attributes.

SAMPLE		ERO		BIOD		FIRE		LAND		TAX	
		TV	% ignored	TV	% ignored	TV	% ignored	TV	% ignored	TV	% ignored
FTF_PT	HH	2.0	12.0	2.0	12.4	2.0	0.0	2.0	0.0	2.0	32.1
	PWRA	3.41	5.8	1.99	12.4	0.50	16.8	0.56	14.2	2.80	20.1
WEB_PT	HH	2.0	6.4	2.0	2.8	2.0	1.4	2.0	9.9	2.0	29.1
	PWRA	1.90	6.4	1.99	3.2	1.05	5.3	2.60	6.4	4.20	9.6
WEB_DE	HH	2.0	2.7	2.0	10.6	2.0	0.0	2.0	0.4	2.0	47.7
	PWRA	1.23	9.5	2.02	10.6	0.69	15.9	1.04	5.3	5.13	15.9

Note: n.a. means non-applicable.

underestimated in the HH approach compared to the PWRA results for the PGaE attributes, and overestimated in the case of the cost attribute. Comparing the PWRA and the HH approaches, the average differences between the percentage of respondents ignoring each attribute were 21% for TAX, 12.1% for FIRE, and 5.2% for LAND; while for the ERO and BIO attributes these differences were under 0.2%.

Therefore, there was marked heterogeneity in the threshold values depending on the inferred ANA approach, attribute and sub-sample. The next section describes how this heterogeneity was reflected in the welfare estimates yielded by both inferred approaches.

5.2. Model results and welfare estimates: Comparison of the approaches that accommodate ANA

In order to assess whether the suggested approach provides a better way to discriminate between respondents attending and non-attending to the attributes, the RPANA models described in the methodological section were estimated for the inferred approaches (HH and PWRA). The performance in terms of ANA identification, parameter significance and goodness of fit of the four RPANA models were compared.

The results of the models (for each sub-sample) are presented in Tables 3–5. The two models were highly significant in terms of parameters and goodness of fit. Overall, in both approaches and sub-samples, the attendance group registered highly significant parameters (below the 0.01% level) for all the attributes and all had the expected sign. Heterogeneity was not present in all approaches and sub-samples although there were on average between three and four attributes with significant standard deviations.

Regarding the non-attendance layer both approaches yielded non-significant monetary attribute. All the parameters for PGaE attributes were significant and negative (except for LAND in the HH approach in the WEB_DE sub-sample). The negative sign for PGaE indicated that respondents prefer less provision of public goods. While a priori this might seem an unexpected result, it offers a practical advantage when exploring this behaviour with the aim of designing public policies. In this regard, both approaches have been able to identify true non-attenders to the monetary attribute (zero marginal utility) and non-compensatory behaviour towards the PGaE. There may be a number of different explanations for these theoretically inconsistent patterns: (i) protest responses, where individuals are against the general idea of implementing

Table 3
RPANA results based on stated and inferred (HH, PWRA) approaches for the FTF_PT sample.

Approaches		HH				PWRA			
Parameters		Mean (μ)		SD (σ)		Mean (μ)		SD (σ)	
		Est.	SE	Est.	SE	Est.	SE	Est.	SE
Attendance	ASC_SQ	−2.021***	0.053			−1.631***	0.560		
	ERO	1.273***	0.205	–	–	1.291***	0.222	1.096***	0.206
	BIOD	1.287***	0.213	0.117***	0.014	1.618***	0.231	0.111***	0.013
	FIRE	1.641***	0.218	1.078***	0.223	2.596***	0.250	–	
	LAND	0.813***	0.226	0.586*	0.301	1.567***	0.248	–	
	TAX	−0.092***	0.015	0.117***	0.014	−0.078***	0.013	0.111***	0.013
Non-attendance	ERO	−2.422***	0.398	–		−2.428***	0.571	–	
	BIOD	−1.558***	0.373	–		−1.495***	0.391	–	
	FIRE	–		–		−0.843***	0.307	–	
	LAND	–		–		−1.973***	0.473	1.176*	0.661
	TAX	−0.013	0.011	–		−0.006	0.013	–	
Goodness of fit	Nr parameters	13				15			
	χ^2 (*p*-value)	1362.642 (0.000)				1478.221 (0.000)			
	McFadden R^2	0.452				0.491			
	Log likelihood (LL)	−823.777				−765.987			
	AIC/n	1.220				1.139			

***, **, * indicate significance at the 1%, 5% and 10% level, respectively. (-) for the standard deviations indicates that the standard deviations are not significant and therefore the parameters have been set as fixed (non-random), while for the non-attendance layer it indicates that there are no respondents ignoring the attribute and therefore the mean parameters cannot be estimated.

programmes financed by taxpayers; (ii) misunderstanding the attribute levels; (iii) the use of specific heuristic patterns to cope with the complexity of the tasks; (iv) lack of interest and/or protest response due to the fact that some attribute levels may be seen as totally unrealistic; or (v) a modelling artefact due to the use of unconstrained normal distributions (using unconstrained normal distributions can have the potential drawback of finding a portion of implausible parameter values). While we acknowledge that we cannot disentangle these potential explanations, it is true that those patterns of behaviour were conflated into the non-attendance layer; thus, their effect can be deducted from the attendance layer. The interested reader can refer to Balbontin et al. (2019) for a review of process heuristics, behavioural refinements, and experience. Regarding the heterogeneity in the parameter estimates (described as the standard deviations), the non-attendance layer had more parameters with non-significant standard deviations than the attendance one, with all the standard deviations of the parameters being non-significant for all the attributes and models (except for the LAND attribute in the FTF_PT for the PWRA analysis).

In the three combinations of sub-samples (FTF_PT, WEB_DE, WEB_PT), the alternative-specific constant for the SQ option (ASC_SQ) was not significant in the PWRA, while it was significant in the HH estimation approach and sub-samples. The ASC_SQ represents the preferences that are inherent to and independent of specific attribute levels. One potential explanation is that the PWRA eliminates the source of heterogeneity derived from the ASC_SQ as it can better identify the two groups of respondents (attendance and non-attendance layer).

In order to highlight the importance of the diagnostic tool developed in this research, the goodness of fit criteria of the models are compared. The PWRA was evidently the best one according to the AIC/n criterion (displaying the lowest level in two of the three sub-samples) and the pseudo-R^2 (notably higher in all three subsamples). Specifically, the PWRA outperformed the HH in the FTF_PT and the WEB_DE samples, while in the WEB_PT sample the goodness of fit was slightly better for the HH. The Vuong test (Vuong, 1989) for model selection was applied in order to statistically determine which methodological approach resulted superior and closer to the true data generating process. This approach for non-nested models tests the null hypothesis that the expected value of the difference vector of log-likelihood ratios for competing models equals zero, indicating that there is no evidence of superior fit among alternative ANA specifications. Results showed that the PWRA outperformed the HH in two of the three sub-samples (FTF_PT and WEB_DE) as the Vuong-test statistic[8] was 3.52, −4.76 and 6.74 for the FTF_PT, WEB_PT and WEB_DE respectively comparing PWRA versus HH.

As the intended contribution of this paper is to develop an analytical tool to customise the HH rule of thumb for identifying ANA, the results of the WTP estimates of the competing inferred approaches are presented in Table 6. The WTP estimates represent the € per household for 100% of the area benefitting from the public good programme. The WTP estimates of the PWRA approach were consistently higher in all sub-samples than those of the HH approach considering ANA. There were statistically significant differences in welfare estimates in 8 of the 12 WTP comparisons (it is only for ERO in FTF_PT and WEB_PT, for BIO in WEB_PT and for LAND in WEB_PT that no statistically significant differences were found). Specifically, the average differences in the PGaE WTP estimates were around €10 for FTF_PT, €22 for WEB_PT

8 A positive (negative) parameter higher (lower) than 1.96 (−1.96) means that the PWRA (HH) outperforms HH (PWRA). The Vuong test is inconclusive at the 5% significance level for the range between −1.96 and 1.96.

Table 4
RPANA results based on stated and inferred (HH, PWRA) approaches for WEB_PT sample.

Approaches		HH				PWRA			
Parameters		Mean (μ)		SD (σ)		Mean (μ)		SD (σ)	
		Est.	SE	Est.	SE	Est.	SE	Est.	SE
Attendance	ASC_SQ	−0.942*	0.488			−0.687	0.481		
	ERO	1.038***	0.186	–		1.099***	0.188		
	BIOD	1.795***	0.202	0.108***	0.012	1.856***	0.205	–	
	FIRE	1.441***	0.181	0.711***	0.220	1.580***	0.188	0.085***	0.009
	LAND	1.468***	0.211	–		1.438***	0.219	0.516*	0.277
	TAX	−0.057***	0.012	0.108***	0.012	−0.035***	0.010	0.800***	0.225
Non-attendance	ERO	−1.658***	0.448	–		−1.692***	0.470	–	
	BIOD	−2.233***	0.683	–		−2.078***	0.666	–	
	FIRE	−2.217***	0.807	–		−1.557***	0.452	–	
	LAND	−2.709***	0.490	–		−2.780***	0.590	–	
	TAX	0.003	0.010	–		0.001	0.012	–	
Goodness of fit	Nr parameters	14				15			
	χ^2 (*p*-value)	1316.398 (0.000)				1257.292 (0.000)			
	McFadden R^2	0.424				0.405			
	Log likelihood (LL)	−890.843				−920.397			
	AIC/n	1.282				1.325			

***, **, * indicate significance at the 1%, 5% and 10% level, respectively. (-) for the standard deviations indicates that the standard deviations are not significant and therefore the parameters have been set as fixed (non-random), while for the non-attendance layer it indicates that there are no respondents ignoring the attribute and therefore the mean parameters cannot be estimated.

Table 5
RPANA results based on stated and inferred (HH, PWRA) approaches for WEB_DE sample.

Approaches		HH				PWRA			
Parameters		Mean (μ)		SD (σ)		Mean (μ)		SD (σ)	
		Est.	SE	Est.	SE	Est.	SE	Est.	SE
Attendance	ASC_SQ	−1.205**	0.486			−0.267	0.481		
	ERO	0.850***	0.185	–		1.288***	0.188	–	
	BIOD	1.976***	0.222	0.150***	0.018	2.374***	0.205	0.084***	0.010
	FIRE	0.741***	0.166	0.540**	0.236	1.333***	0.188	–	
	LAND	1.109***	0.213	0.650***	0.248	1.604***	0.219	–	
	TAX	−0.087***	0.019	0.150***	0.018	−0.027***	0.010	0.084***	0.010
Non-Attendance	ERO	−3.516***	0.878	–		−2.162***	0.470	–	
	BIOD	−1.747***	0.376	–		−1.175***	0.666	–	
	FIRE	–	–	–		−1.123**	0.452	–	
	LAND	−3.403	2.358	–		−2.695***	0.590	–	
	TAX	−0.002	0.009	–		0.004	0.012	–	
Goodness of fit	Nr parameters	14				13			
	χ^2 (*p*-value)	1137.958 (0.000)				1230.550 (0.000)			
	McFadden R^2	0.392				0.424			
	Log likelihood (LL)	−881.189				−834.892			
	AIC/n	1.355				1.283			

***, **, * indicate significance at the 1%, 5% and 10% level, respectively. (-) for the standard deviations indicates that the standard deviations are not significant and therefore the parameters have been set as fixed (non-random), while for the non-attendance layer it indicates that there are no respondents ignoring the attribute and therefore the mean parameters cannot be estimated.

and €60 for WEB_DE. These results can be explained by the differences between the HH and PWRA in the percentage of respondents that were classified as non-attenders to the cost attribute.

To give an overview of the phenomenon, if the three sub-samples are pooled, the average levels of non-attenders to the cost attribute were 36.3% and 15.2% for HH and PWRA approaches, respectively. This effect is particularly salient for the WEB_DE survey, where the percentage of respondents not attending the cost attribute was 47.3% for HH versus 15.9% for PWRA. Therefore, the PWRA is better able to isolate the share of respondents with low disutility for the cost attribute, avoiding a potential confounding effect between genuine non-attendance and taste heterogeneity. This translates into lower disutility for the cost attribute in the PWRA approach than in the HH approach, reflected in higher WTP vectors for the former. Regarding the PGaE, no clear trend emerges from the comparison of the percentage in each layer (attenders versus non-attenders) in the HH and PWRA; therefore, the results are sample- and attribute-dependent. Thus, a clear pattern cannot be established, unlike with the cost attribute, where the custom PWRA seems reasonably consistent in not confounding low disutility with zero utility (non-attendance).

Table 6
WTP estimates (mean and 90% confidence intervals) and results of Poe test for differences between the HH and PWRA.

FTF_PT				
	ERO	BIOD	FIRE	LAND
HH	14.20[a] (8.10–20.91)	14.37 [a] (9.06–21.31)	18.25[a] (12.22–26.32)	9.12[a] (4.23–15.06)
PWRA	17.11[a] (9.99–26.93)	21.52[a] (13.74–32.34)	34.29[b] (23.76–48.91)	20.88[b] (12.69–31.92)
WEB_PT				
HH	19.62[a] (10.69–35.08)	33.45[a] (20.56–54.96)	26.85[a] (16.50–44.61)	27.10[a] (16.06–47.02)
PWRA	36.33[a] (16.54–72.73)	60.39[b] (31.16–115.18)	51.15[b] (27.11–98.44)	47.21[a] (22.16–93.45)
WEB_DE				
HH	10.43[a] (5.57–17.37)	22.03[a] (15.32–36.14)	9.00[a] (4.56–14.96)	13.53[a] (7.63–22.40)
PWRA	54.29[b] (23.40–139.40)	98.71[b] (48.06–230.80)	55.31[b] (25.43–138.67)	66.82[b] (30.11–172.27)

Note: All WTP estimates are different from zero at the 0.1% significance level according to the Krinsky and Robb (1986) procedure with 1000 simulations. Within each attribute and sub-sample different subscript letters means that the HH and PWRA WTP estimations are significantly different at the 90% level according to the Poe test (Poe et al., 2005).

6. Discussion and conclusions

In this paper, we have continued the line of research of Hess and Hensher (2010), who seek to distinguish between respondents attending to/ignoring different attributes by using the individual CV to determine when the conditional mean is indistinguishable from zero. Hess and Hensher (2010) apply the arbitrary threshold of 2 for the CV to distinguish between respondents' behaviour. It has been developed a diagnostic tool to fine-tune this threshold iteratively in various sub-samples, based on piecewise regression analysis (PWRA).

The threshold values estimated using the PWRA are attribute- and sample-specific and, therefore, differ between attributes and samples; nonetheless, in most of the cases, they are lower than the threshold value of 2 proposed by Hess and Hensher (2010). Likewise, according to the goodness of fit assessment and the Vuong test results, the PWRA outperforms the HH approach in two out of the three sub-samples, indicating its usefulness in providing a more comprehensive representation of the random heterogeneity.

Thus, the use of PWRA to determine custom threshold values emerges as a promising way to deal with the ANA phenomenon displaying how the PWRA outperforms the HH approach in revealing the true model. In this regard, it seems reasonable to advise the use of the PWRA approach instead of applying a fixed threshold that cannot account for attribute- and sample-specific variability. Likewise, it is advisable to compare the results of the PWRA approach in terms of parameter estimates and percentage of people ignoring each attribute with those of alternative, inferred ANA strategies, such as the popular constrained latent class model (Scarpa et al., 2013; Kragt, 2013) or the more recent Generalised Random Parameter Attribute Non-Attendance model (Collins et al., 2013). Therefore, the use of the PWRA to determine custom threshold values emerges as a promising way to deal with the ANA phenomenon.

In the welfare analysis, we assume that the group of respondents not considering the monetary attribute either reflect an inconsistency from an economic theory perspective or indicate that the levels of the monetary attribute are not relevant for some respondents, representing a stated preference artefact rather than real life behaviour (Hensher et al., 2012; Hess et al., 2013). If these aspects are not properly addressed, it would lead to implausible and theoretically unsound welfare estimates (cases of infinitely high WTP could potentially occur, biasing the welfare population estimates). On the other hand, as discussed by Hole et al. (2013) and Hess et al. (2013), what is really relevant in demand contexts is to develop a modelling strategy that accurately accounts for ANA and does not confound taste heterogeneity (low sensitivity) with non-attendance (zero sensitivity), due to the implications for welfare estimations. In our analysis, the proportion of respondents ignoring the cost attribute with the HH approach is notably and consistently higher than with the PWRA. This is arguably a strong indication that the HH rule of thumb is especially imprecise for the cost attribute, generating an upward bias in the level of non-attendance. This finding supports the claim by HH that the rule of thumb of 2 is very conservative, with a resulting risk of classifying individuals who just have a low sensitivity (utility or disutility) to the cost attribute as non-attenders. This misclassification is translated to the WTP estimates, which are systematically higher with the PWRA approach than the HH approach, as respondents with low sensitivity to the cost attribute are classified as non-attenders in the HH approach and are, therefore, not considered in the WTP estimations. Thus, the use of the HH approach may well generate a downward bias in the welfare measures, negatively influencing the size of the budget allocated to the design of efficient public policies for the provision of public goods. Therefore, keeping observations with virtually zero disutility in the calculation of welfare measures is as inappropriate as employing a very rough rule of thumb that confounds taste heterogeneity with non-attendance. The proposal developed here allows the researcher to customise the threshold separating taste heterogeneity (low sensitivity) from true non-attendance behaviour. One avenue for further methodological research is to analyse alternative specifications of the stepwise regression, for example using non-linear approaches.

Regarding the factors affecting ANA, the study by Balbontin and Hensher (2021) in the context of business location concludes that both the attribute levels and the experimental design characteristics (e.g. choice-set number) determine stated ANA. Therefore, in future research, it would be interesting to assess whether the experimental design characteristics also influence inferred ANA, as it may have a bearing on the ANA diagnostic tool developed in this paper. Such an assessment would require an experimental design in which the DCE design characteristics vary among treatments (e.g. range of attributes, number of levels, etc.).

To conclude, we call for further research to test the diagnostic tool for identifying ANA presented in this paper with other databases, settings and modelling approaches. We believe that it is a promising option given its robustness, versatility and potential for customisation. In this regard, it is highly likely that in most of the studies carried out with the popular random parameter logit models, the level of heterogeneity is heavily inflated by neglecting to account for ANA. The proposed diagnostic tool is able to identify ANA patterns — irrespective of the potential explanations. This approach helps ensure a more accurate estimation of the welfare measures and therefore provides more precise information to policy-makers. As such, it is critical to replicate this approach in different DCE settings since it will enable the further development of the method and will offer external validity.

Acknowledgements

The authors are solely responsible for the content of the paper. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission. The authors are particularly grateful to the anonymous referees for their very helpful comments on the previous versions of the paper.

Appendix A

See Table 7.

Table 7
Socio-demographic characteristics.

		FTF_PT		WEB_PT		WEB_DE	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
AGE	Age (continuous variable)	42.88	13.78	35.67	10.17	42.44	13.33
EDU	Education (ordinal scale 1–8, increasing levels)	5.61	1.73	6.27	1.42	4.05	1.57
GEN*	Gender (dichotomous variable, 1 if male)	0.49	0.50	0.53	0.50	0.51	0.50
DEP	Dependants under 16 years (continuous variable)	1.54	0.87	1.61	0.84	1.41	0.81
INC	Income level (ordinal variable 1–6, increasing categories	3.27	1.02	3.04	1.05	3.44	1.27
VIS	Number of visits to the Mediterranean region in the last 5 years (continuous variable)	1.51	1.12	1.85	1.30	1.23	1.73
EMP	Employment status (dichotomous variable, 1 if employed)	0.80	0.27	0.63	0.34	0.75	0.25
FAR*	Working in the farming sector (dummy coded variable, 1 if yes);	0.01	0.10	0.01	0.08	0.00	0.06
ENT	Working as an entrepreneur (dummy coded variable, 1 if yes);	0.04	0.21	0.10	0.30	0.08	0.27
ADM	Working in an administrative role (dummy coded variable, 1 if yes);	0.15	0.36	0.00	0.00	0.20	0.40
SCI	Working as a scientist/academic (dummy coded variable, 1 if yes);	0.24	0.43	0.35	0.48	0.06	0.23
SER	Working in the service sector (dummy coded variable, 1 if yes);	0.13	0.34	0.10	0.30	0.27	0.44
Sample size (n)			274		282		264

Note: * Denotes variables where there are no significant differences among the 3 samples (Bonferroni-corrected t-test to account for multiple comparisons).

Appendix B

See Tables 8–10.

Table 8
RPLM results of the FTF_PT sample.

	Coef.	SE	p-value
Mean value			
ERO	0.214	0.547	0.695
BIOD	1.730	0.205	0.000
FIRE	1.770	0.307	0.000
LAND	1.890	0.207	0.000
TAX	−0.034	0.007	0.000
Heterogeneity in mean			
EROxEDU	0.204	0.089	0.022
EROxADM	0.783	0.406	0.053
EROxSER	0.162	0.472	0.043
FIRExINC	0.274	0.082	0.048
FIRExVIS	0.954	0.140	0.050
LANDxSCI	−0.580	0.321	0.070
Standard deviations			
ERO	1.303	0.252	0.000
BIOD	1.846	0.264	0.000
FIRE	1.090	0.287	0.000
LAND	0.799	0.277	0.004
TAX	0.084	0.010	0.000
Goodness of fit			
Nr observations	1370		
$\chi 2$ (p-value)	1139.0369 (0.000)		
Mc-Fadden R^2	0.378		

Table 9
RPLM results of the WEB_PT sample.

	Coef.	SE	p-value
Mean value			
ERO	−0.276	0.521	0.595
BIOD	2.003	0.177	0.000
FIRE	−0.009	0.642	0.988
LAND	1.517	0.168	0.000
TAX	−0.023	0.006	0.000
Heterogeneity in mean			
EROxEDU	0.220	0.082	0.007
FIRExEDU	0.196	0.088	0.026
FIRExDEP	0.297	0.153	0.052
TAXxENT	0.034	0.021	0.099
Standard deviations			
ERO	0.759	0.222	0.000
BIOD	1.263	0.222	0.000
FIRE	0.981	0.239	0.000
LAND	1.365	0.231	0.000
TAX	0.074	0.009	0.000
Goodness of fit			
Nr observations	1410		
χ^2(p-value)	1040.874 (0.000)		
Mc-Fadden R^2	0.335		

Table 10
RPLM results of the WEB_DE sample.

	Coef.	SE	p-value
Mean value			
ERO	0.880	0.136	0.000
BIOD	3.103	0.540	0.000
FIRE	0.982	0.117	0.000
LAND	1.515	0.146	0.000
TAX	−0.023	0.007	0.000

(*continued on next page*)

Table 10 (*continued*).

	Coef.	SE	*p*-value
Heterogeneity in mean			
EROxENT	0.502	0.260	0.007
BIODxAGE	−0.023	0.011	0.026
TAXxVIS	0.006	0.003	0.052
Standard deviations			
ERO	0.725	0.238	0.002
BIOD	1.655	0.218	0.000
FIRE	0.589	0.266	0.026
LAND	0.940	0.230	0.000
TAX	0.059	0.008	0.000
Goodness of fit			
Nr observations	1320		
χ^2(*p*-value)	878.785 (0.000)		
Mc-Fadden R^2	0.302		

Appendix C

See Table 11.

Table 11
PWRA estimates.

		ERO	BIOD	FIRE	LAND	TAX
FTF_PT	Parameter					
	a_1	153.8	30.347	1.481	1.705	36.245
		(1.938)	(0.601)	(0.035)	(0.048)	(0.937)
	b_1	−3372.0	−117.7	−0.570	−0.95	−4068.8
		(61.130)	(3.188)	(0.025)	(0.047)	(165.8)
	C	0.045	0.241	1.719	1.205	0.008
		(0.000)	(0.002)	(0.028)	(0.017)	(0.000)
	b_2	−1.352	−0.581	−0.132	−0.232	−22.602
		(0.118)	(0.029)	(0.004)	(0.008)	(2.413)
	F-test					
	F-value	2738.58	1156.19	978.93	1053.69	606.26
	Model df/error df	3/270	3/270	3/270	3/270	3/270
	Approx. PR>F	<.0001	<.0001	<.0001	<.0001	<.0001
WEB_PT	Parameter					
	a_1	33.581	36.989	9.543	238.3	290.3
		(0.548)	(0.385)	(0.139)	(1.770)	(6.630)
	b_1	−299.4	−217.8	−21.0904	−4630.6	−225274
		(8.954)	(4.616)	(0.569)	(47.091)	(10908.3)
	C	0.106	0.131	0.403	0.051	0.001
		(0.001)	(0.001)	(0.006)	(0.000)	(0.000)
	b_2	−1.116	−0.427	−0.374	−1.129	−42.116
		(0.092)	(0.023)	(0.017)	(0.120)	(17.367)
	F-test					
	F-value	1668.20	4694.6	2020.83	6382.83	736.86
	Model df/error df	3/278	3/280	3/278	3/278	/3/278
	Approx. PR>F	<.0001	<.0001	<.0001	<.0001	<.0001
WEB_DE	Parameter					
	a_1	9.198	50.247	1.896		130.0
		(0.187)	(0.758)	(0.043)		(3.1363)
	b_1	−23.596	−384.6	−1.610		−55496.9
		(0.773)	(11.109)	(0.065)		(2301.5)
	C	0.338	0.125	0.751		0.003
		(0.005)	(0.002)	(0.008)		(0.000)
	b_2	−0.724	−0.568	−0.495		−66.247
		(0.036)	(0.058)	(0.013)		(13.486)
	F-test					
	F-value	1034.37	1874.03	1399.04		638.49

(*continued on next page*)

Table 11 (*continued*).

	ERO	BIOD	FIRE	LAND	TAX
Model df/error df	3/260	3/260	3/260		3/260
Approx. PR>F	<.0001	<.0001	<.0001		<.0001

Note: The parameters of the PWRA correspond to the following regression functions, which are continuous at the breakpoint (when x=c): $y = a_1 + b_1 x$, *for* $x \leq c$ and $y = a_1 + c(b_1 - b_2) + b_2 x$, *for* $x > c$; where: $y = cv_{kn}$; $x = \mu_{kn}$; c = breakpoint and a_1, b_1 and b_2 are the parameters to be estimated. The standard errors are displayed in parentheses.

Appendix D

See Table 12.

Table 12
Threshold values of the CV for different percentiles of respondents attending each attribute.

% of respondents attending	FTF_PT					FTF_DE					WEB_DE				
	ERO	BIOD	FIRE	LAND	TAX	ERO	BIOD	FIRE	LAND	TAX	ERO	BIOD	FIRE	LAND	TAX
5%	0.38	0.38	0.26	0.32	0.35	0.41	0.35	0.33	0.38	0.43	0.40	0.34	0.41	0.36	0.43
10%	0.40	0.42	0.29	0.34	0.42	0.43	0.37	0.35	0.39	0.50	0.44	0.36	0.43	0.38	0.52
15%	0.42	0.47	0.30	0.35	0.50	0.45	0.39	0.38	0.46	0.65	0.46	0.37	0.45	0.41	0.69
20%	0.46	0.49	0.31	0.35	0.69	0.47	0.40	0.39	0.50	0.74	0.49	0.39	0.47	0.45	0.88
25%	0.48	0.51	0.32	0.36	0.89	0.49	0.42	0.41	0.53	0.88	0.53	0.41	0.49	0.46	1.08
30%	0.52	0.57	0.34	0.37	0.97	0.50	0.43	0.42	0.56	1.02	0.55	0.43	0.51	0.48	1.23
35%	0.56	0.61	0.35	0.38	1.01	0.52	0.46	0.44	0.58	1.11	0.57	0.46	0.54	0.49	1.38
40%	0.58	0.68	0.36	0.39	1.08	0.56	0.49	0.45	0.61	1.20	0.60	0.49	0.55	0.51	1.51
45%	0.62	0.71	0.37	0.40	1.31	0.59	0.51	0.47	0.63	1.32	0.63	0.54	0.56	0.52	1.67
50%	0.65	0.76	0.38	0.41	1.50	0.61	0.53	0.49	0.66	1.43	0.68	0.58	0.57	0.53	1.93
55%	0.69	0.81	0.40	0.42	1.60	0.64	0.55	0.51	0.75	1.51	0.71	0.61	0.59	0.55	2.08
60%	0.74	0.92	0.40	0.43	1.67	0.68	0.57	0.54	0.88	1.60	0.75	0.66	0.59	0.58	2.23
65%	0.82	1.11	0.42	0.44	1.91	0.70	0.59	0.58	1.05	1.78	0.79	0.71	0.60	0.63	2.54
70%	0.89	1.21	0.44	0.46	2.09	0.75	0.62	0.61	1.11	1.91	0.82	0.80	0.61	0.67	2.91
75%	1.00	1.51	0.46	0.48	2.54	0.84	0.66	0.63	1.22	2.18	0.85	0.89	0.63	0.70	3.37
80%	1.17	1.77	0.48	0.53	2.82	0.98	0.72	0.67	1.38	2.75	0.93	1.02	0.66	0.74	4.11
85%	1.44	1.88	0.51	0.55	3.38	1.08	0.83	0.74	1.58	3.30	1.06	1.42	0.69	0.77	5.63
90%	2.43	2.08	0.55	0.62	5.08	1.30	0.95	0.86	1.91	3.86	1.21	2.13	0.74	0.86	10.18
95%	5.20	2.89	0.66	0.76	6.97	2.20	1.16	1.07	3.44	7.52	1.49	3.39	0.82	1.05	17.54
100%	128.07	26.24	1.19	1.24	46.52	31.87	28.35	9.28	212.24	364.12	9.46	45.70	1.27	14.86	190.00

Note: As 100% represent all the respondents, the Table can be as well interpreted as the % of respondents ignoring each attribute. As an example, if the threshold value for the CV is 2.43 for ERO in the FTF_PT sample; 90% of respondents will be attending the attribute and therefore 10% of respondents ignoring it.

References

Alemu, M.H., Morkbak, M.R., Olsen, S.B., Jensen, C.L., 2013. Attending to the reasons for attribute non-attendance in CE. Environ. Resour. Econ 54 (3), 333–359.

Andreoni, J., 1990. Impure altruism and donations to public goods: A theory of warm-glow giving. Econ. J 100 (401), 464–477.

Balbontin, C., Hensher, D., 2021. Understanding business location decision making for transport planning: An investigation of the role of process rules in identifying influences on firm location. J. Transp. Geogr. 91, 102955.

Balbontin, C., Hensher, D., A., Collins, 2019. How to better represent preferences in choice models: The contributions to preference heterogeneity attributable to the presence of process heterogeneity. Transp. Res. Part B: Methodol. 122, 218–248.

Barrio, M., Loureiro, M., 2013. The impact of protest responses in choice experiments: an application to a biosphere reserve management program. Forest. Syst 22 (1), 94–105.

Bello, M., Abdulai, A., 2016. Impact of ex-ante hypothetical bias mitigation methods on attribute non-attendance in choice experiments. Amer. J. Agric. Econ. 98 (5), 1486–1506.

Campbell, D., Hensher, D.A., Scarpa, R., 2011. Non-attendance to attributes in environmental choice analysis: A latent class specification. J. Environ. Plann. Manag 54 (8), 1061–1076.

Campbell, D., Hutchinson, W.G., Scarpa, R., 2008. Incorporating discontinuous preferences into the analysis of discrete choice experiments. Environ. Resour. Econ 41 (3), 401–417.

Caputo, V., Nayga, R.M., Scarpa, R., 2013. Food miles or carbon emissions? Exploring labelling preference for food transport footprint with a stated choice study. Australian J. Agric. Resour. Econ 57 (4), 465–482.

Carlsson, F., Kataria, M., Lampi, E., 2010. Dealing with ignored attributes in choice experiments on valuation of Sweden's environmental quality objectives. Environ. Resour. Econ 47 (1), 65–89.

Chalak, A., Abiad, M., Balcombe, K., 2016. Joint use of attribute importance rankings and non-attendance data in choice experiments. Eur. Rev. Agric. Econ 43 (5), 737–760.

Collins, A.T., Rose, J.M., Hensher, D.A., 2013. Specification issues in a generalised random parameters attribute nonattendance model. Transp. Res. B 56, 234–253.

Colombo, S., Glenk, K., 2013. Social preferences for agricultural policy instruments: Joint consideration of non-attendance to attributes and to alternatives in modelling discrete choice data. J. Environ. Plann. Manag 57 (2), 215–232.

Colombo, S., Glenk, K., Rocamora-Montiel, B., 2016. Analysis of choice inconsistencies in on-line choice experiments: Impact on welfare measures. Eur. Rev. Agric. Econ 43 (2), 271–302.

De Bekker-Grob, E., Ryan, M., Gerard, K., 2012. Discrete choice experiments in health economics: A review of the literature. Health Econ 21 (2), 145–172.

Espinosa-Goded, M., Barreiro-Hurlé, J., 2010. Las preferencias discontinuas en los experimentos de elección: Impacto en el cálculo de la prima de los programas agroambientales. Econ. Agrar. Recur. Nat. 10 (1), 155–176.

Espinosa-Goded, M., Barreiro-Hurlé, J., Ruto, E., 2010. What do farmers want from agri-environmental scheme design? A choice experiment approach. J. Agric. Econ 61 (2), 259–273.

European Commission, 2019a. Agri-environment measures. Available at: https://ec.europa.eu/agriculture/envir/measures_en (Accessed 22 2019).

European Commission, 2019b. The common agricultural policy at a glance. Availabe at: https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/cap-glance_en#howitspaidfor (Accessed 22 2019.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., Tatham, R.L., 2019. Multivariate Data Analysis, Eight ed. Cengage, Hampshire, UK.

Hensher, D., Collins, A.T., Greene, W., 2013. Accounting for attribute non-attendance and common-metric aggregation in a probabilistic decision process mixed multinomial logit model: a warning on potential confounding. Transportation 40 (5), 1003–1020.

Hensher, D.A., Rose, J.M., Greene, W.H., 2005. The implications of willingness to pay of respondents ignoring specific attributes. Transportation 32, 203–222.

Hensher, D., Rose, J., Greene, W., 2012. Inferring attribute non-attendance from stated choice data: Implications for willingness to pay estimates and a warning for stated choice experiment design. Transportation 39, 235–245.

Hensher, D.A., Rose, J.M., Greene, W.H., 2015. Applied Choice Analysis, second ed. Cambridge University Press, Cambridge, UK.

Hensher, D., Truong, T., 1985. Valuation of travel time savings: a direct experimental approach. J Transp. Econ. Policy 19 (3), 237–261.

Hess, S., Hensher, D., 2010. Using conditioning on observed choices to retrieve individual-specific attribute processing strategies. Transp. Res. B 44, 781–790.

Hess, S., Hensher, D.A., 2013. Making use of respondent reported processing information to understand attribute importance: a latent variable scaling approach. Transportation 40 (2), 397–412.

Hess, S., Stathopoulos, A., D., Campbell., O'Neil.l, V., Caussade, S., 2013. It is not that I do not care, I just don't care very much: confounding between attribute non-attendance and taste heterogeneity. Transportation 40 (3), 583–607.

Hole, A.R., 2011. A discrete choice model with endogenous attribute attendance. Econom. Lett. 110 (3), 203–205.

Hole, A.R., Kolstad, J.R., Gyrd-Hansen, D., 2013. Inferred vs. stated attribute non-attendance in choice experiments: a study of doctors' prescription behaviour. J. Econ. Behav. Org. 96, 21–31.

Hole, A.R., Norman, R., Viney, R., 2016. Response patterns in health state valuation using endogenous attribute attendance and latent class analysis. Health Econ 25 (2), 212–224.

Kragt, M., 2013. Stated and inferred attribute attendance models: a comparison with environmental choice experiments. J. Agric. Econ 64 (3), 719–736.

Kravchenko, A., 2014. Influence of rudimentary attribute non-attendance (ANA) on choice experiment parameter estimates and design efficiency: A Monte Carlo simulation analysis. J. Choice Model. 11, 57–68.

Krinsky, I., Robb, A.L., 1986. On approximating the statistical properties of elasticities. Rev. Econ. Stat 68 (4), 715–719.

Leong, W., Hensher, D.A., 2012. Embedding decision heuristics in discrete choice models: A review. Transp. Rev 32 (3), 313–331.

Lew, D.K., Whitehead, J.C., 2020. Attribute non-attendance as an information processing strategy in stated preference choice experiments: Origins, current practices, and future directions. Marine Res. Econ. 35 (3), 195–200.

Madureira, L., Lima-Santos, J., Ferreira, A., Guimaraes, H., Espinosa-Goded, M., Gómez y Paloma, S., 2013. Feasibility Study on the Valuation of Public Goods and Externalities in EU. JRC Scientific and Technical Report. EUR 83468 EN, Publications Office of the European Union, Luxembourg.

Mariel, P., Hoyos, D., Meyerhoff, J., 2013. Stated or inferred attribute non-attendance? A simulation approach. Econ. Agrar. Recur. Nat. 13 (1), 51–67.

Moré, J.J., 1978. In: Watson, G.A. (Ed.), The Levenberg–Marquardt Algorithm: Implementation and Theory. In: Lecture notes in mathematics., Springer-Verlag, Berlin-Heidelberg-New York.

Neter, J., Wasserman, W., Kutner, M.H., 1990. Applied linear statistical models: regression, analysis of variance, and experimental designs. Irwin, Illinois.

Ortega, D.L., Ward, P.S., 2016. Information processing strategies and framing effects in developing country choice experiments: Results from rice farmers in India. Agric. Econ 47 (5), 493–504.

Poe, G.L., Giraud, K.L., Loomis, J.B., 2005. Computational methods for measuring the difference of empirical distributions. Am. J. Agric. Econ 87 (2), 353–365.

Puckett, S.M., Hensher, D.A., 2009. Revealing the extent of process heterogeneity in choice analysis: An empirical assessment. Transp. Res. A 43, 117–126.

Rodríguez-Entrena, M., Villanueva, A.J., Gómez-Limón, J.A., 2019. Unravelling determinants of inferred and stated attribute non-attendance: effects on farmers' willingness to accept to join agri-environmental schemes. Can. J. Agric. Econ 67, 31–52.

Rose, J.M., Bliemer, M.C.J., 2009. Constructing efficient stated choice experimental designs. Transp. Rev 9 (5), 587–617.

SAS Institute Inc., 2015. SAS/STAT® 14.1 User'S Guide. SAS Institute Inc., Cary, NC.

Scarpa, R., Gilbride, T.J., Campbell, D., Hensher, D.A., 2009. Modelling attribute non-attendance in choice experiments for rural landscape valuation. Eur. Rev. Agric. Econ 36, 151–174.

Scarpa, R., Philipidis, G., Spalatro, F., 2005. Product-country images and preference heterogeneity for mediterranean food products: A discrete choice framework. Agribusiness 21 (3), 329–349.

Scarpa, R., Zanoli, R., Bruschi, V., Naspetti, S., 2013. Inferred and stated attribute non-attendance in food choice experiments. Am. J. Agric. Econ 95, 165–180.

Thiene, M., Scarpa, R., Louviere, J.J., 2015. Addressing preference heterogeneity, multiple scales and attribute attendance with a correlated finite mixing model of tap water choice. Environ. Resour. Econ. 62 (3), 637–656.

Train, K., 2003. Discrete Choice Methods with Simulation. Cambridge University Press, Cambridge, UK.

Villanueva, Anastasio J., Glenk, Klaus, Rodríguez-Entrena, Macario, 2017. Protest Responses and Willingness to Accept: Ecosystem Services Providers' Preferences towards Incentive-Based Schemes. J. Agric. Econ. 68 (3), 801–821. http://dx.doi.org/10.1111/1477-9552.12211.

Villanueva, A.J., Gómez-Limón, J.A., Rodríguez-Entrena, M., 2017. Heterogeneity of farmers' preferences towards agri-environmental schemes across different agricultural subsystems. J. Environ. Plann. Manag 60 (4), 684–707.

Vuong, Q.H., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. Econometrica 57, 307–333.