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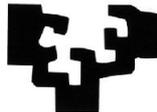
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Comparing the performance of different approaches to deal with attribute non-attendance in discrete choice experiments: a simulation experiment.

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Comparing the performance of different approaches to deal with attribute non-attendance in discrete choice experiments: a simulation experiment

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Abstract

There is a growing body of literature acknowledging that respondents to DCE often use simplifying strategies, like ignoring one or several attributes to provide with their choices. Two main approaches have appeared to analyse the impact of attribute non-attendance on welfare estimates: the stated non-attendance (SNA) approach and the analytical non-attendance (ANA) approach. Using simulation experiments, this paper investigates the results and reliability of the approaches developed in the recent years in order to deal with attribute non-attendance. The simulation results indicate that the treatments so far proposed are not in all cases suitable. In the absence of correlated errors, the SNA approach seems to provide with unbiased welfare estimates but the ANA approach fails to do so. On the other hand, in the presence of correlated errors, none of the approaches seems to provide with unbiased WTP estimates in all cases.

Keywords: discrete choice experiments, simulation; attribute non-attendance, willingness to pay

JEL: Q51

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1. Introduction

The Discrete Choice Experiment (DCE) methodology is a fast growing environmental valuation technique. Initially developed by Louviere and Hensher (1982) and Louviere and Woodworth (1983), the first application of a DCE in the context of environmental resources was reported by Adamowicz et al. (1994). Since then, the number of applications has significantly increased and DCE have become a popular stated preference method for environmental valuation.

Recently, a growing body of literature has highlighted that respondents to DCE often ignore one or several attributes when stating their choices. Some reasons for ignoring attributes include the use of simplifying strategies, to protest against the trade-off between money and the environment by ignoring the cost attribute, lexicographic ordering due to an unbalanced importance of the proposed attributes or that respondents are simply not willing to pay anything for this attribute (Carlsson et al., 2009). The implications of this problem are threefold: First, from a behavioural perspective, it implies non-compensatory behaviour. Second, from a theoretical point of view, ignoring attributes posses some challenges to the neoclassical economic theory because it violates the continuity axiom. And third, from a policy perspective, not accounting for attribute non-attendance may provide with biased welfare measures and, as a consequence, it may result in misguided policies.

Two main approaches have appeared in the literature to analyse the impact of attribute non-attendance on welfare estimates: the stated non-attendance (SNA) approach and the analytical non-attendance (ANA) approach. So far all studies that deal with attribute non-attendance have reported that it indeed takes place; however, it is not yet clear whether the so far proposed treatments of non-attendance bias WTP estimates themselves. So, using simulation experiments, this paper investigates the results and reliability of both approaches dealing with this issue.

The rest of the paper is structured as follows. Section 2 reviews the state of the art on this issue. Section 3 describes how the simulation experiments were designed. Section 4 reports

and discusses the main results. Finally, Section 5 concludes by summarising the main findings of the paper.

2. Literature review

Process heterogeneity with respect to attribute non-attendance has received increasing attention in the last few years. In general, two approaches analysing the impact of attribute non-attendance in choice experiments exist. First, respondents are directly asked whether they have considered all attributes describing the alternatives of the choice tasks or whether they have ignored one or more attributes while choosing among the alternatives of a choice task (stated non-attendance (SNA) approach). Second, studies have applied analytical models and defined rules recognising attribute non-attendance (analytical non-attendance (ANA) approach). These studies do not rely on self-stated non-attendance. This overview commences with studies that employed the SNA approach and proceeds with those that used the ANA approach. Table 1 summarises the results of the overview.

Among the first who explicitly investigated the implications of ignored attributes were Hensher et al. (2005). Based on supplementary information from commuters they estimate models (i) assuming that all attributes have been attended and (ii) that some attributes were ignored. Comparing the values of travel time saving from both models they conclude that not accounting for attribute non-attendance leads to significantly higher willingness to pay (WTP) estimates. Campbell et al. (2008) asked respondents in a survey concerning improvements of rural landscapes after the sequence of choice tasks whether they considered all attributes. If not, respondents were required to indicate which attributes they had not taken into account. While 64% considered all attributes the remaining 36% were assumed to have discontinuous preferences. Overall, the cost attribute was the least attended attribute. Their estimations show that accounting for attribute non-attendance results in better goodness-of-fit and lower WTP estimates. For their most informed model these estimates were up to 60% lower compared to an uninformed model.

Also Carlsson et al. (2009) incorporated information about attribute non-attendance analysing three choice experiments regarding a balanced marine environment in the Baltic sea, flourishing lakes and streams, and clean air. They requested respondents after the choice tasks to indicate whether they ignored any of the attributes and, if so, to name them. Comparing informed and uninformed models they were not able to reject the null hypothesis of equality for any of the marginal WTP estimates between the two models for all three choice

experiments. Kosenius (2008) use information from two mutually exclusive attribute processing strategies. One strategy is to attend all attributes and the second is to attend only those attributes that were perceived as more important than the other attributes. In the choice experiment on eutrophication levels in the Gulf of Finland more than half of the respondents stated that at least one attribute was more important to them than the other attributes. Marginal WTP estimates from naïve and informed models resulted in different values with the latter between 15 and 67% higher as from the naïve model.

Campbell and Lorimer (2009) use both the SNA as well as the ANA approach. Respondents were asked after the choice tasks about attendance of attributes but the authors as well employ an analytical approach checking if respondents were "doing what they were saying". The responses show that interviewees do not attend all attributes and are likely to adapt an attribute processing strategy to ease their decision-making. At the same time the random parameter logit models, accounting for heterogeneity in both preferences and attribute processing strategies, indicate that some discrepancy exists between the self-stated responses and the attribute processing strategy picked up by their model. Thus, while recognising that the self-stated non-attendance improved model performance and lowered the WTP estimates in the order of three times the magnitude, the authors conclude that the so far standard approach of asking respondents about attribute non-attendance may not adequately reflect the heterogeneity in processing strategies.

In contrast to asking respondents after all choice tasks a couple of studies have recently asked respondents after each choice task to indicate attribute non-attendance. Puckett and Hensher (2009) analyse data from a survey of road freight transport providers in Sydney, Australia, acknowledging that varying process rules may be enacted not only across decision makers but also across choice tasks given faced by a given decision maker. They reveal considerable heterogeneity in attribute exclusion strategies across respondents and choice sets as well as an overestimation of the value of travel time savings when process heterogeneity is ignored. Meyerhoff and Liebe (2009) monitor non-attendance after each choice task in survey concerning the landscape externalities of wind power. According to their results only a minority ignores the same attributes on each of the five choice tasks presented. Informed models show slightly better performance but the marginal WTP estimates are not significantly different.

Kaye-Blake et al. (2009), using a computerised information display board, found as well that accounting for respondents information use affects modelling results, but that the impact on estimates of WTP may be relatively small. They valued various potato types differing by, e.g.,

texture, nutrition, country of origin, and price. The information display board aims to reveal the information respondents have used and thus does not require posterior self-reporting. Access to the information was captured for each attribute of every alternative. Over the whole dataset, just over one-fifth of the available information was not assessed. Scarpa et al. (2009) use data from a choice experiment about multiple park management services. Respondents were invited to state those attributes they did not attend after each choice task. Based on this information they investigated the implications of choice-task non-attendance and serial non-attendance. The latter is reconstructed for those attributes ignored throughout the whole sequence of choice tasks. Their findings highlight that substantial intra-panel variation is present, i.e., respondents do not ignore always the same attributes on the choice tasks presented, that accounting for choice task non-attendance significantly improves the fit of the estimated models and that results in a more plausible pattern of marginal WTP values.

The studies investigating non-attendance using analytical models mainly employ latent class logit models (LCM). Campbell (2008) uses a latent class specification in order to derive individual-specific probabilities of respondents not attending a certain attribute. For each of the attributes of a DCE concerning endangered fish species, a two-class model was estimated in which in one class the coefficient for the respective attribute was set to zero while in the other class all coefficients were estimable. Subsequently, the probabilities were used to condition the attribute parameters in a multinomial error component logit model. Campbell finds that accommodating the strength of non-attendance of each respondent's preferences leads to significant improvements in model performance and that the magnitude and robustness of the WTP estimates is sensitive to non-attendance. Hensher et al. (2009) as well employ the latent class logit model but recognise non-attendance of different attributes in one model. They define classes based on rules acknowledging the non-attendance of one or more attributes. Each class in this model with overall seven classes represents a particular process heuristic ranging from a class where all attributes have been attended to classes where one particular attributes or all attributes were not attended. The authors find a probability in excess of 80 per cent that a sample respondent did not considered all attributes. Compared with a naïve multinomial logit model the marginal estimates vary significantly for specific attributes.

Also Hensher and Greene (2009) define in a latent class framework classes based on rules recognising attribute non-attendance of one or more attributes and on the addition and the parameter transfer of common metric attributes. They find a probability in excess of 74 per cent that a sample respondent has applied one of the defined attribute processing rules. Their

WTP estimates for travel time savings from the informed model are on average significantly higher than those from an uninformed model. Finally, Scarpa et al. (2009) propose two ways of modelling attribute non-attendance. Their first approach is similar to Hensher et al. (2009) and Hensher and Greene (2009) using a latent class logit model. The second approach is based on stochastic attribute selection and grounded in Bayesian estimation. According to Scarpa et al. both approaches produce concordant results suggesting that attribute non-attendance is frequent, treatment and identification are relevant for estimation outcomes as they significantly improve goodness-of-fit and the efficiency of coefficient estimates, and strongly affect the estimation of non-market values. Only 10 per cent of their respondents acted to the conventional assumption of considering all attributes and, most alarming for environmental valuation, the money coefficient appears to have been ignored by 80 to 90 per cent of the respondents.

Table 1: Summary of studies dealing with attribute non-attendance

Author	Year	Field	Survey method	Follow-up question?	Analytical Modelling	Model	Non-attendance	Impact on WTP?	Performance increase?
Campbell	2008	E	NR	No	No	LCM/ ECL	Yes	Yes	Yes
Campbell & Lorimer	2009	E	NR	Yes (serial)	No	RPL	Yes	Yes	Yes
Campbell et al.	2008	E	F-to-F	Yes (serial)	No	ECL	Yes	Yes	Yes
Carlsson et al.	2009	E	Mail	Yes (serial)	No	RPL	Yes	Nn	No
Hensher & Greene	2009	T	F-to-F (CAPI)	No	Yes	LCM	Yes	Yes	Yes
Hensher et al.	2009	E	F-to-F (CAPI)	No	Yes	LCM	Yes	Yes	Yes
Hensher et al.	2005	T	F-to-F (CAPI)	Yes (serial)	No	RPL	Yes	Yes	Yes (small)
Kaye-Blake et al.	2009	F	F-to-F (CAPI)	No	No	RPL	Yes	Yes	Yes
Kosenius	2008	E	Mail	Yes (serial)	No	RPL	Yes	Yes	No
Meyerhoff & Liebe	2009	E	Phone/ mail	Yes (task)	no	ECL	Yes	No	Yes (small)
Puckett & Hensher	2009	T	F-to-F (CAPI)	Yes (task)	No	ECL	Yes	Yes	NR
Scarpa et al.	2009	E	F-to-F	Yes (task)*	Yes	LCM Bayesian	Yes	Yes	Yes
Scarpa et al.	forthcoming	E	F-to-F	Yes (task)	No	MNL	Yes	Yes	Yes

Field   E (Environment, T (Transportation), F (Food)
Survey   F-to-F (Face-to-Face)
Follow-up   Serial (after all choice sets), task (after each choice set)
Model   MNL (Multinominal Logit Model), LCM (Latent Class Logit Model), RPL (Random Parameter Logit Model), ECL (Error Component Logit Model)
NR   Not reported
*   Information not used in analysis

Overall, the present state of the literature strongly suggests that respondents do not consider all attributes when choosing among the alternatives presented in a choice set. A subgroup of respondents uses different attribute processing strategies, i.e., they do not attend all attributes. This subgroup can, in some cases, amount to the majority of respondents. More recent studies indicate that non-attendance takes rather place at the choice task level as respondents do not ignore the same attributes at each choice task. Moreover, accounting for non-attendance, regardless whether the stated or the analytical approach are employed, generally improves model performance and influences in the greater number of cases WTP significantly estimates. Whether the stated or the analytical approach is better suited to capture the effects of attribute non-attendance is still an open question. Only one study presents evidence that a discrepancy exists between self-stated responses and the attribute processing strategies picked-up by the model. Thus, comparisons between stated and analytical approaches to capture as well as developing suitable approaches to monitor attribute non-attendance remains as an important topic for future research.

3. Design of the simulation experiments

The simulation experiments were based on a model attempting to generate a typical discrete choice experiment used in environmental valuation. For this purpose, it included three alternatives, status quo (SQ) and two non-labelled alternatives (ALT1, ALT2), each containing four attributes (three environmental attributes and the cost attribute). The following table summarises the attributes and levels considered in the design:

Table 2. Experimental design used for the simulations

Attribute 1 (ATTR1)	Attribute 2 (ATTR2)	Attribute 3 (ATTR3)	Cost (COST)
0	10	60	0
20	30	70	30
40	50	80	60
60	70	90	90
80	90	100	120

The utility functions were assumed to be linear in attributes and they were defined as:

$$U(SQ) \quad = \beta_0 + \beta_1 ATTR1 + \beta_2 ATTR2 + \beta_3 ATTR3 + \beta_4 COST + \varepsilon_{SQ}$$
$$U(ALT1) = \quad\;\; \beta_1 ATTR1 + \beta_2 ATTR2 + \beta_3 ATTR3 + \beta_4 COST + \varepsilon_{ALT1} \qquad (1)$$
$$U(ALT2) = \quad\;\; \beta_1 ATTR1 + \beta_2 ATTR2 + \beta_3 ATTR3 + \beta_4 COST + \varepsilon_{ALT2}$$

where all ε are iid random variables following Extreme Value distribution with location parameter equal to 0 and scale parameter equal to 1 and parameters β were set to:

β_0	β_1	β_2	β_3	β_4
0.5	0.01	0.01	0.01	-0.01

In this simple setting, a MNL model estimation leads to WTP estimates equal to one for the three attributes. In order to test our scripts, an experiment based on MNL estimation and using 1600 simulated (and not correlated in any way) hypothetical responses repeated 1000 was carried out. Figure 1 shows a box-plot of the three simulated distributions of WTP.

Figure 1: WTP distributions, MNL, Full attendance
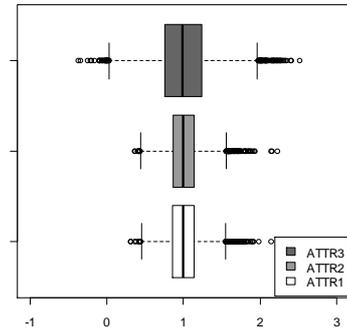
Note that the three WTP distributions in Figure 1: are centred on the true value one and the WTP corresponding to the third attribute present wider spread caused by wider variance of the estimation of β_3 due to the use of a narrower range of the levels in the this attribute.

The second set of simulations attempted to incorporate correlated errors. This takes three forms: (1) correlation due to a panel data setting, (2) correlation of the non-SQ utilities and (3) correlation due to a panel data setting and among the non-SQ utilities.

In the first case, it is assumed that each respondent was asked four times (panel data setting) and that is why the error terms of each utility function of model (1) are correlated. It is assumed that the four errors ε_{SQ} corresponding to the four utility U(SQ) of each hypothetical

respondent are correlated and this correlation is set to be 0.8. The same correlations due to four consecutive responses is assumed for the remaining errors ε_{ALT1} and ε_{ALT2}.

In the second case, it is assumed that the utility from the experimentally designed hypothetical alternatives (ALT1 and ALT2) are more correlated amongst themselves than with the utility associated with the status-quo alternative. It is captured by a specification with additional errors accounting for this difference in correlation across utilities. Correlation is a consequence of the fact that the experimental alternatives share this extra error component, that is:

$$
\begin{aligned}
U(SQ) \quad &= \beta_0 + \beta_1 ATTR1 + \beta_2 ATTR2 + \beta_3 ATTR3 + \beta_4 COST + \varepsilon_{SQ} \\
U(ALT1) &= \qquad \beta_1 ATTR1 + \beta_2 ATTR2 + \beta_3 ATTR3 + \beta_4 COST + \eta + \varepsilon_{ALT1} \\
U(ALT2) &= \qquad \beta_1 ATTR1 + \beta_2 ATTR2 + \beta_3 ATTR3 + \beta_4 COST + \eta + \varepsilon_{ALT2}
\end{aligned}
\tag{2}
$$

where η is the error component used to induce correlation amongst the non-SQ alternatives and it is assumed to be $\eta \sim N(0,1)$.

Finally, in the third case, both simulations are combined so that it is incorporated correlation among individuals' responses and non-SQ utilities. So, on the one hand it is assumed that the four errors ε_{SQ} corresponding to the four utility U(SQ) of each hypothetical respondent are correlated and this correlation is set to be 0.8. The same correlations due to four consecutive responses is assumed for the remaining errors ε_{ALT1} and ε_{ALT2}. And, on the other hand, it is assumed that the utility from the experimentally designed hypothetical alternatives (ALT1 and ALT2) are more correlated amongst themselves than with the utility associated with the status-quo alternative.

Once more, in order to prove our scripts we carried out an experiment based on 1600 correlated hypothetical responses generated 1000 times. In this simple case when all attributes are fully attended, the estimation of Model (2) by Error Component Logit (ECL) in panel data setting leads to unbiased WTP estimations (see Figure 2).

Figure 2: WTP distributions, ECL, Full attendance
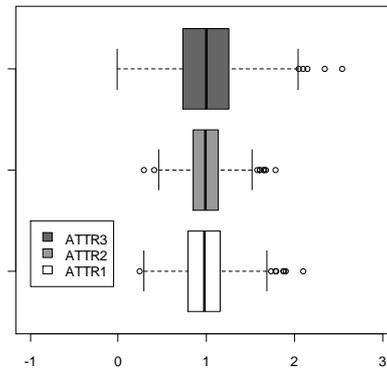
4. Results

According to the base designs described in the previous section, this section will analyse the effects on parameter estimates and welfare measures of the presence of attribute non-attendance and its different treatments. For this purpose, it is assumed in our simulation exercises described below that the first attribute (ATTR1) or the first three attributes (ATTR1, ATTR2, ATTR3) were not attended by our hypothetical respondents and the assumed non attendance percentages are 20%, 40% and 60%.

In the first subsection it is further assumed that the error terms are not correlated, while the second subsection allows for some correlation between the error terms. In both subsections the simulations are divided in two parts: in the first part attribute non-attendance is treated following the stated non-attendance (SNA) approach, and in the third part, attribute non-attendance is treated following the analytical non-attendance (ANA) approach using a LCM specification.

4.1. Non-correlated errors

In the first place, it is assumed that the first attribute was not attended by 20%, 40% and 60% of hypothetical respondents randomly distributed in ATTR1. In all simulation exercises presented in this paper, 1600 hypothetical responses were generated 1000 times, so that all figures presented below show box-plot of 1000 estimates based on these generated responses. Figure 3 presents simulated WTPs based on multinomial logit estimation where no action to treat the non-attendance in attribute ATTR1 was taken. The estimated WTP of

attribute ATTR1 strongly underestimate the true value one and the underestimation bias of the WTP estimates is similar to the value of the percentage of non-attended responses. The coefficients of fully attended attributes are slightly affected.

Figure 3: WTP distributions, MNL, ATTR1 Non-attended, No action
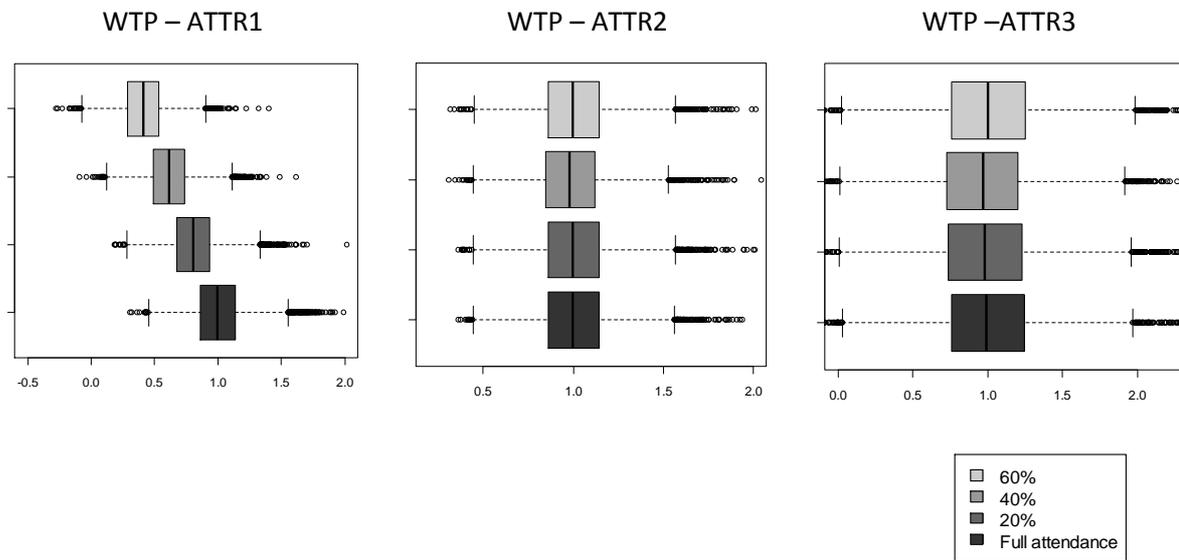
Next, attribute non-attendance is treated following the SNA approach. For this purpose, utility functions defined in (1) are re-specified as to incorporate the attribute parameters as a function of a dummy variable representing whether or not the attribute was considered by the respondent. Following Hensher et al (2005), for these models the choice probabilities are constructed in such a way that the actual elements of the vector of coefficients that enter the likelihood function are set to zero in cases where the element is associated with an attribute ignored by corresponding respondent (Cambell, Hutchinson and Scarpa, 2008). This is easily implemented in the software package NLOGIT (Greene, 2007) by coding non-responses by "-888". Applying this dummy variable approach to the Model (1), the estimated parameters presents astonishing precision in the coefficient estimates which obviously leads to unbiased and precise estimation of WTP. That is, in the case of non-correlated errors this treatment works well and is able to handle non-attendance. Accordingly, the WTP estimates presented in Figure 4 show a perfect correction of non-attendance using the SNA approach.

Figure 4: WTP distributions, MNL, ATTR1 Non-attended, SNA approach
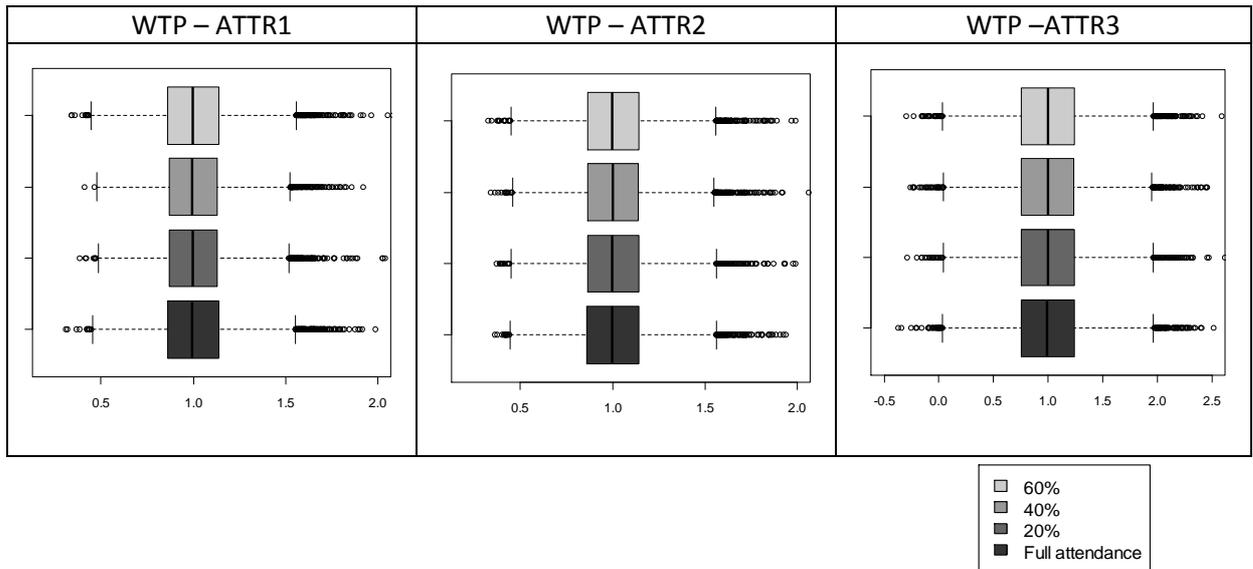
However, the question that can arise after this simple case is whether this treatment works also in cases where all attributes present non-attendance. A simulation experiment similar to the previous one was carried out assuming that the three attributes ATTR1, ATTR2 and ATTR3 are not fully attended and present 60% of non-attendance. The results obtained were similar to those presented above, showing that in this case the SNA approach is robust irrespectively of the number of non-attended attributes.

The second approach applied to this simple case described by model (1) is the ANA approach. Following a latent class model specification, specific restrictions are imposed on the utility expressions for each attribute attendance class in order to represent hypotheses on group adoption of pre-defined processing strategies. In our case, there are two classes defined: in the first class all parameters are unrestricted assuming that all attributes were attended and in the second class β_1 is restricted to zero assuming that ATTR1 was not attended by all respondents. In the first class the population WTP is one for all attributes and in the second class the WTP is obviously zero for the first attribute and one for the remaining two attributes. Figure 5 represents the WTP for both classes. Note that the latent class approach does not solve the problem of non-attendance as WTP of ATTR1 is biased and that the remaining WTPs present high dispersion.

Figure 5: WTP distributions, LCM, ATTR1 Non-attended, ANA approach
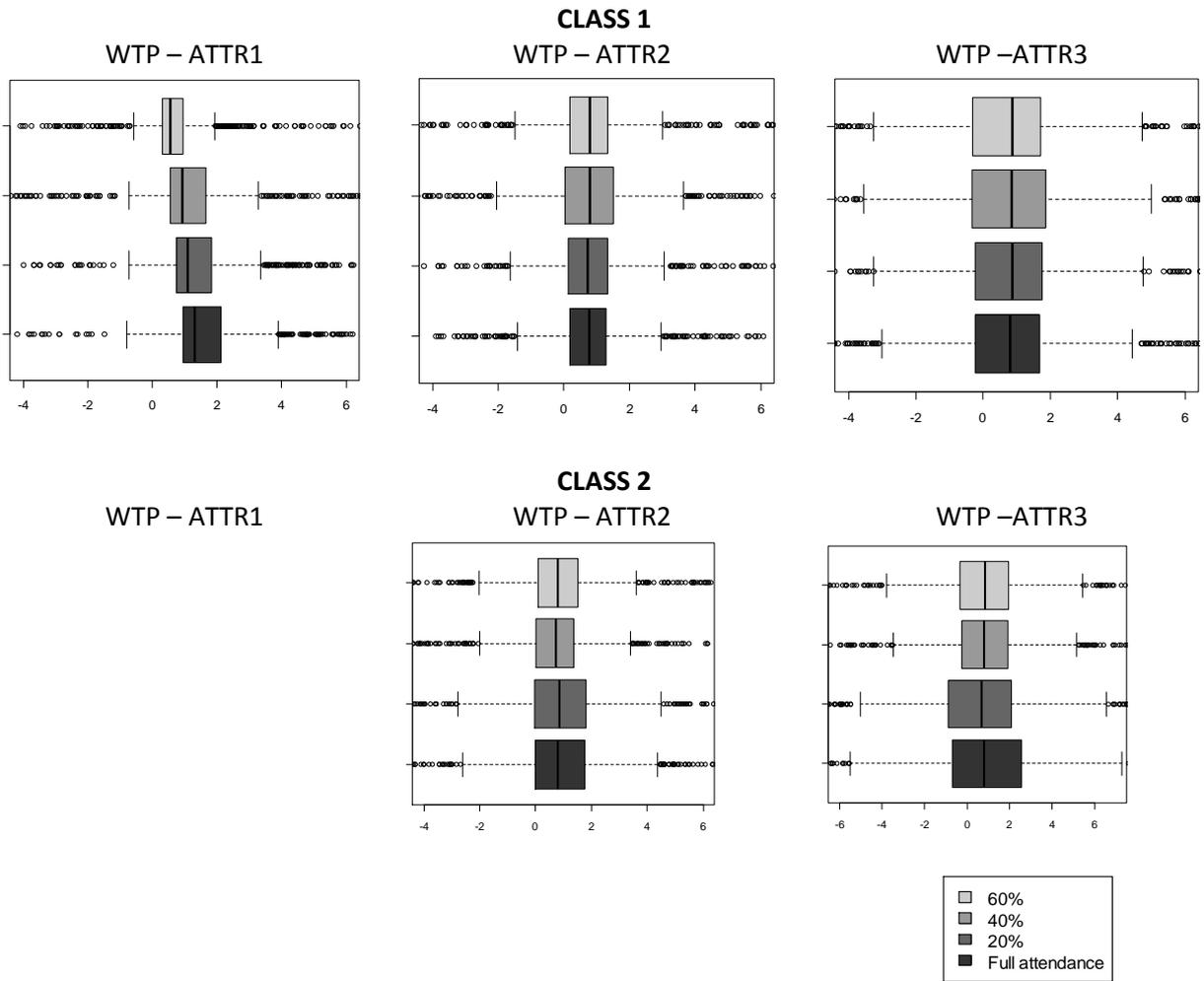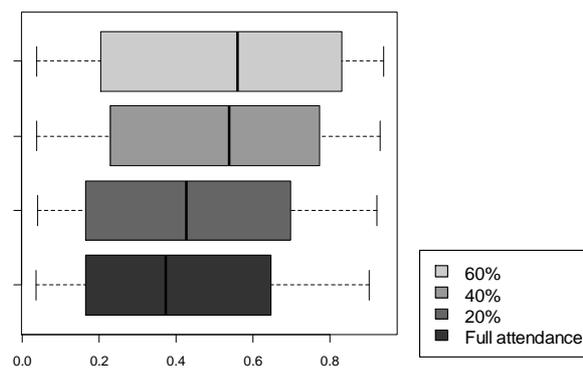
CLASS 1

CLASS 2

Figure 6 presents the probabilities of belonging to the class with the coefficient of the first attribute equal to zero. Even though they should be 0%, 20%, 40% and 60%, the figure shows that these probabilities are not correctly estimated while they also present high volatility.

Figure 6: LCM, ATTR1 Non-attended, Probabilities to belong to the class

4.2. Correlated errors

In the following set of simulations, correlated errors are incorporated. As mentioned in section 3, this is done in three different ways: (1) in the first case, correlation is due only to a panel data structure, (2) in the second case, correlation occurs among the non-SQ utility functions and (3) in the third case correlation is due to both a panel data setting and among the non-SQ utilities. For the three cases, the SNA and ANA approaches are presented.

4.2.1. Panel data setting

In this subsection, the performance of the SNA and ANA approaches will be discussed under the assumption that correlation is due to a panel data setting. As shown in Figure 7, the SNA approach fails to accommodate attribute non-attendance and the WTP estimates for the ignored attribute are overestimated.

Figure 7: WTP distributions, ECL, ATTR1 non-attended, SNA approach
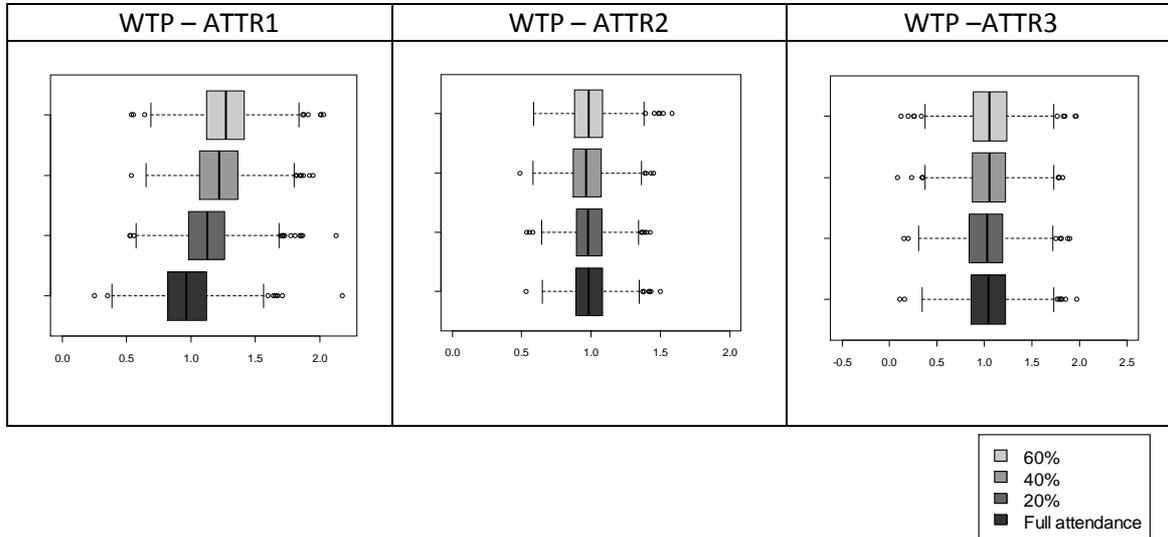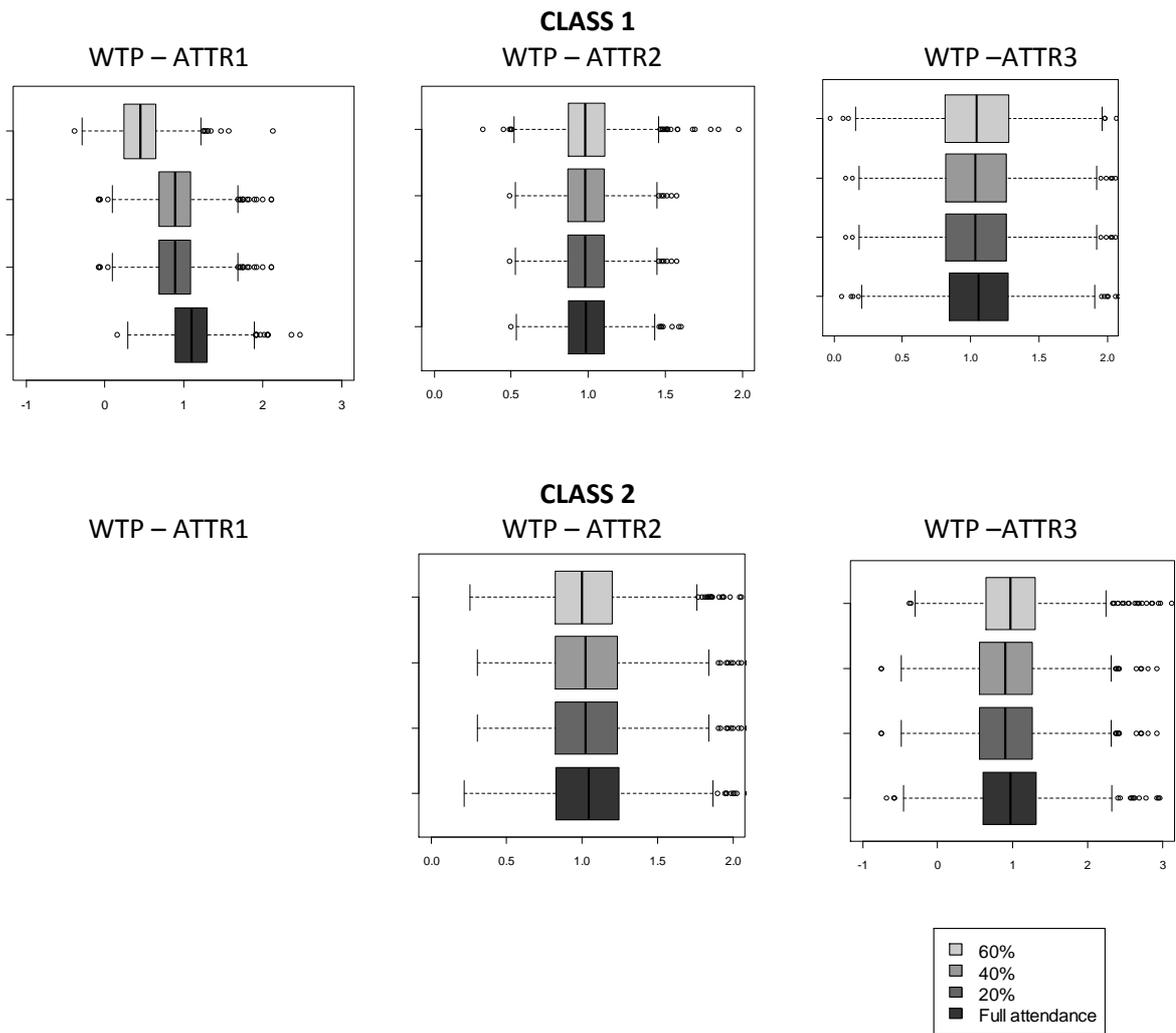

Figure 8 shows that the ANA approach following a latent class model specification also fails to accommodate attribute non-attendance. In this case, the WTP estimates of not fully attended cases corresponding to the first attribute in Class 1 underestimates the true value one.

Figure 8: WTP distributions, LCM, ATTR1 non-attended, ANA approach

CLASS 1

| WTP – ATTR1 | WTP – ATTR2 | WTP –ATTR3 |

CLASS 2

| WTP – ATTR1 | WTP – ATTR2 | WTP –ATTR3 |

☐ 60%
▨ 40%
▨ 20%
■ Full attendance

Next, the probabilities of belonging to the class are estimated. Figure 9 presents these probabilities of belonging to the class with the coefficient of attribute equal to zero which should be 0%, 20%, 40% and 60% but, as shown below, these probabilities are not estimated correctly.

Figure 9: ECL, ATTR1 Non-attended, Probabilities to belong to the class
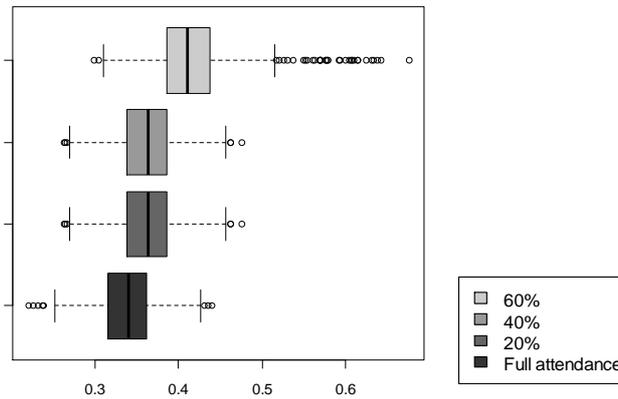
4.2.2. Correlation of non-SQ utilities

In this subsection, the performance of the SNA and ANA approaches will be discussed under the assumption that correlation is now due to the non-SQ utilities, as explained in section 3. Contrary to the results obtained in the previous section, the SNA approach seems to correctly deal with attribute non-attendance and it provides with unbiased parameter estimates (see Figure 10). However, the ANA approach using a LCM specification fails once more to provide with unbiased welfare estimates and it seems to not to estimate correctly the probabilities of belonging to the Class (see Figures 11 and 12).

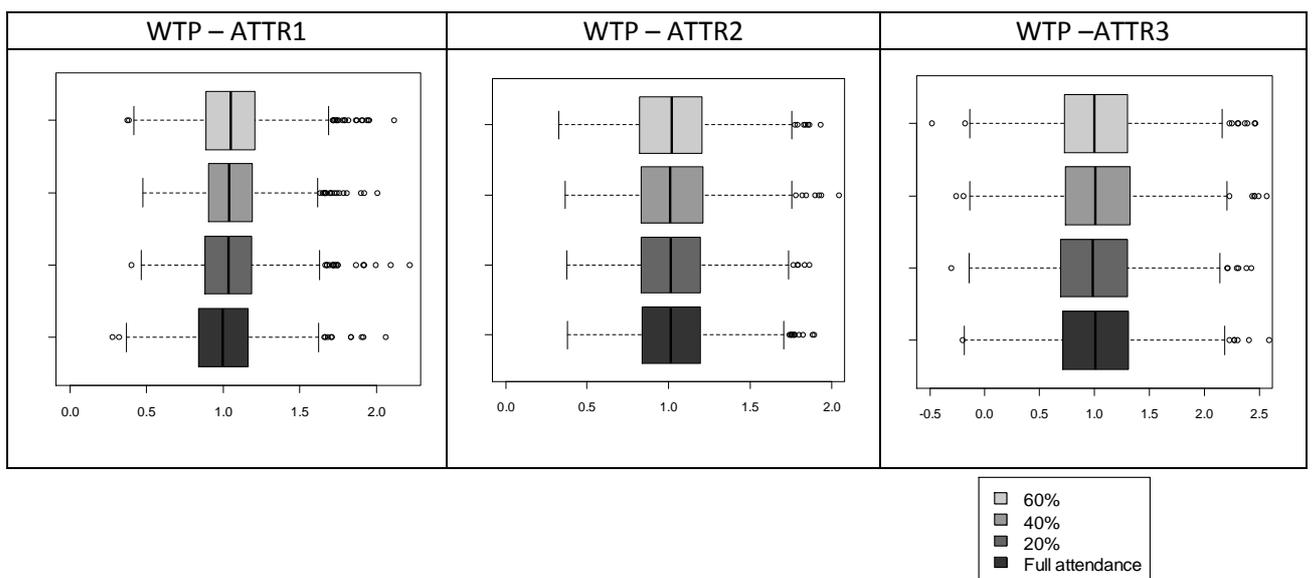**Figure 10: WTP distributions, ECL, ATTR1 non-attended, SNA approach**

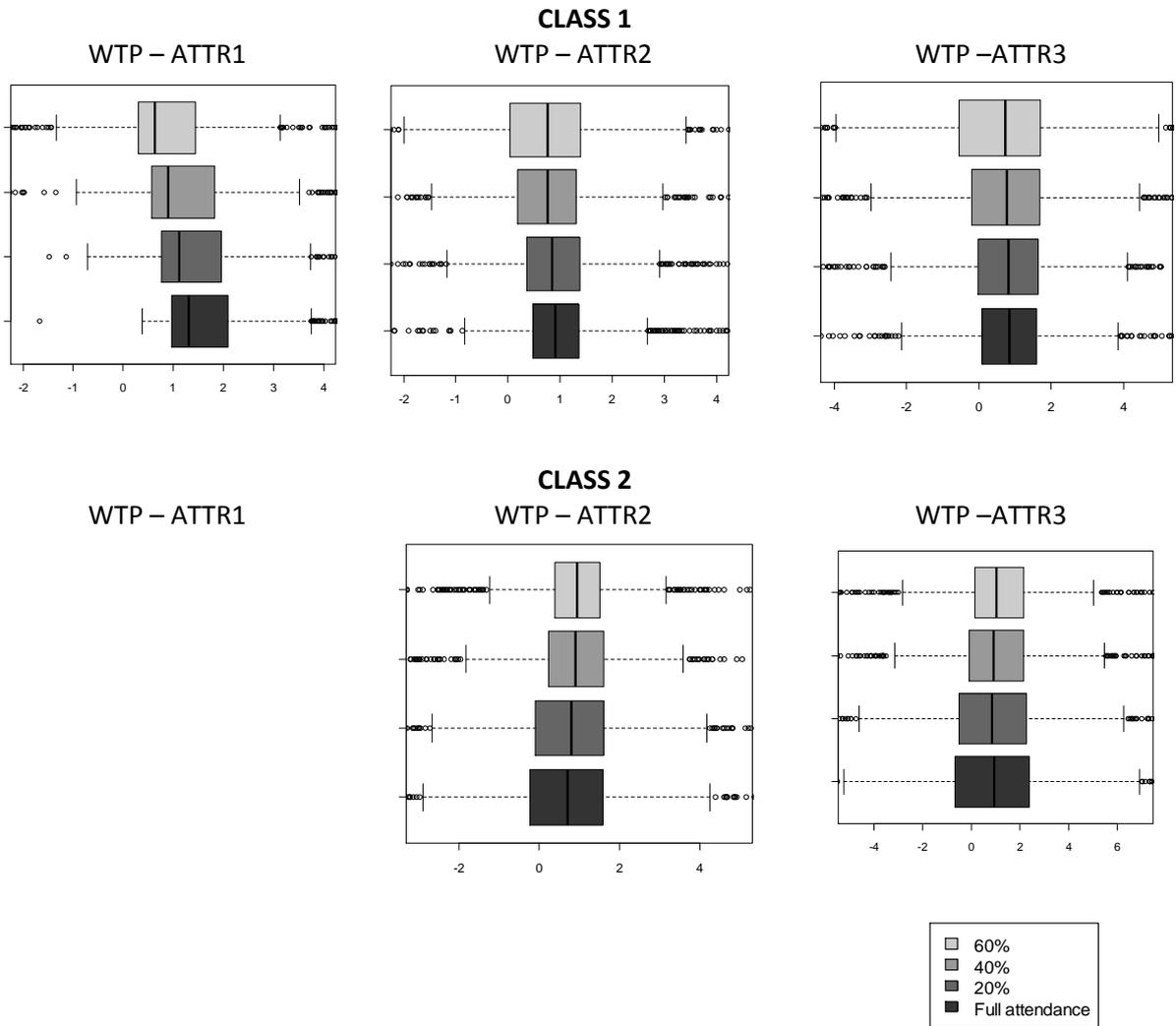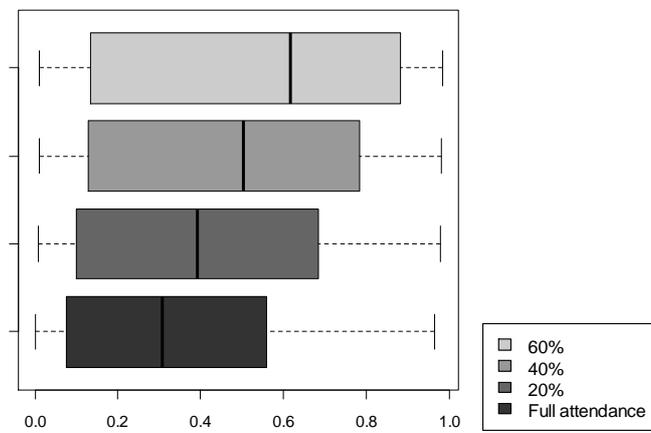**Figure 11: WTP distributions, LCM, ATTR1 non-attended, ANA approach**

CLASS 1

WTP – ATTR1   WTP – ATTR2   WTP –ATTR3

CLASS 2

WTP – ATTR1   WTP – ATTR2   WTP –ATTR3

- 60%
- 40%
- 20%
- Full attendance

Figure 12: ECL, ATTR1 Non-attended, Probabilities to belong to the class

- 60%
- 40%
- 20%
- Full attendance

### 4.2.3. Panel data setting with correlation of non-SQ utilities

Finally, correlation due to both panel data setting and among non-SQ utility functions is simulated. First, the SNA approach is taken in order to deal with the ignoring of the first attribute. As it was the case in previous subsection, the SNA approach does not solve this problem and WTP estimates for the ignored attribute are overestimated (see Figure 13).

Figure 13: WTP distributions, ECL, ATTR1 non-attended, SNA approach
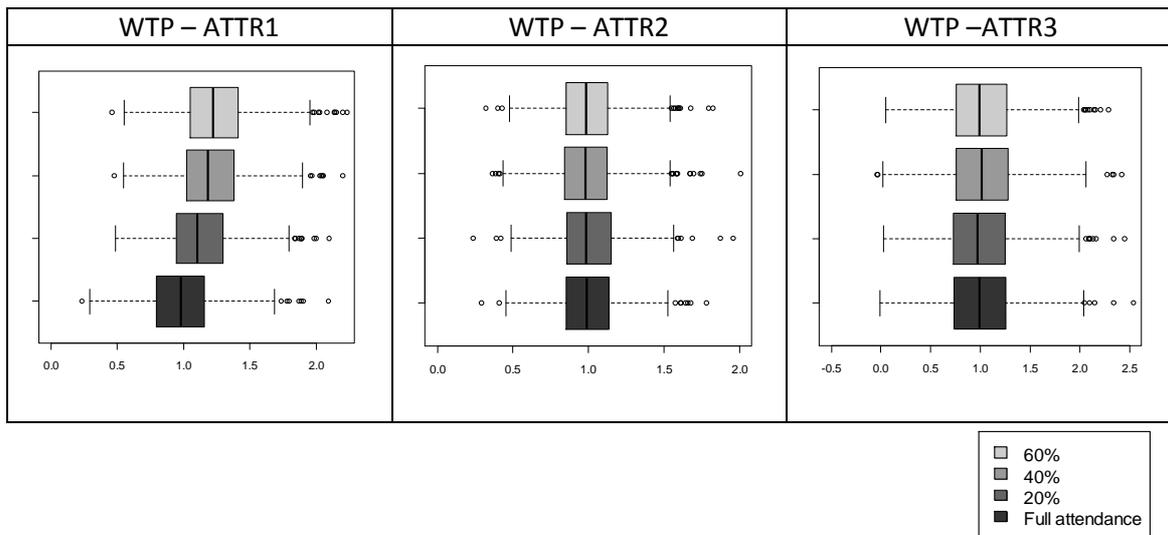

Furthermore, if the three attributes are not attended, the results for this dummy variable approach with ECL are even worse, as expected, and as it can be seen in Figure 14 because the overestimation appear in all three WTP distributions.

Figure 14: WTP distributions, ECL, ATTR1, ATTR2 and ATTR3 non-attended, SNA approach
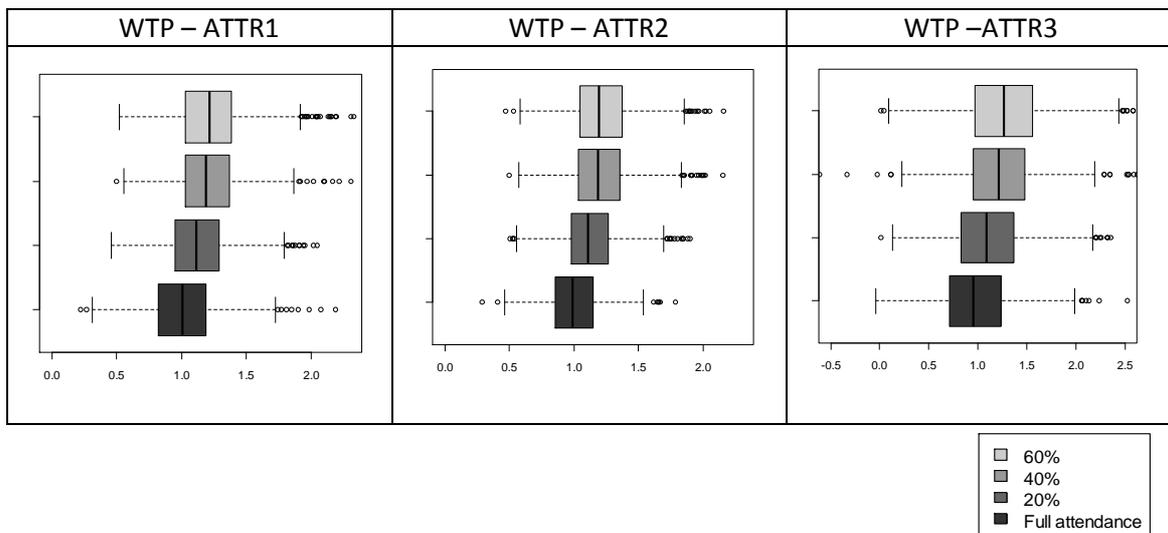
The Latent class model estimation (ANA approach) leads to the WTPs estimations presented in Figure 15. Once more, the WTP corresponding to the first attribute is biased in the Class 1 and WTPs of the remaining two attributes in the second class are affected too but to a lesser extent.

Figure 15: WTP distributions, ECL, ATTR1 non-attended, ANA approach
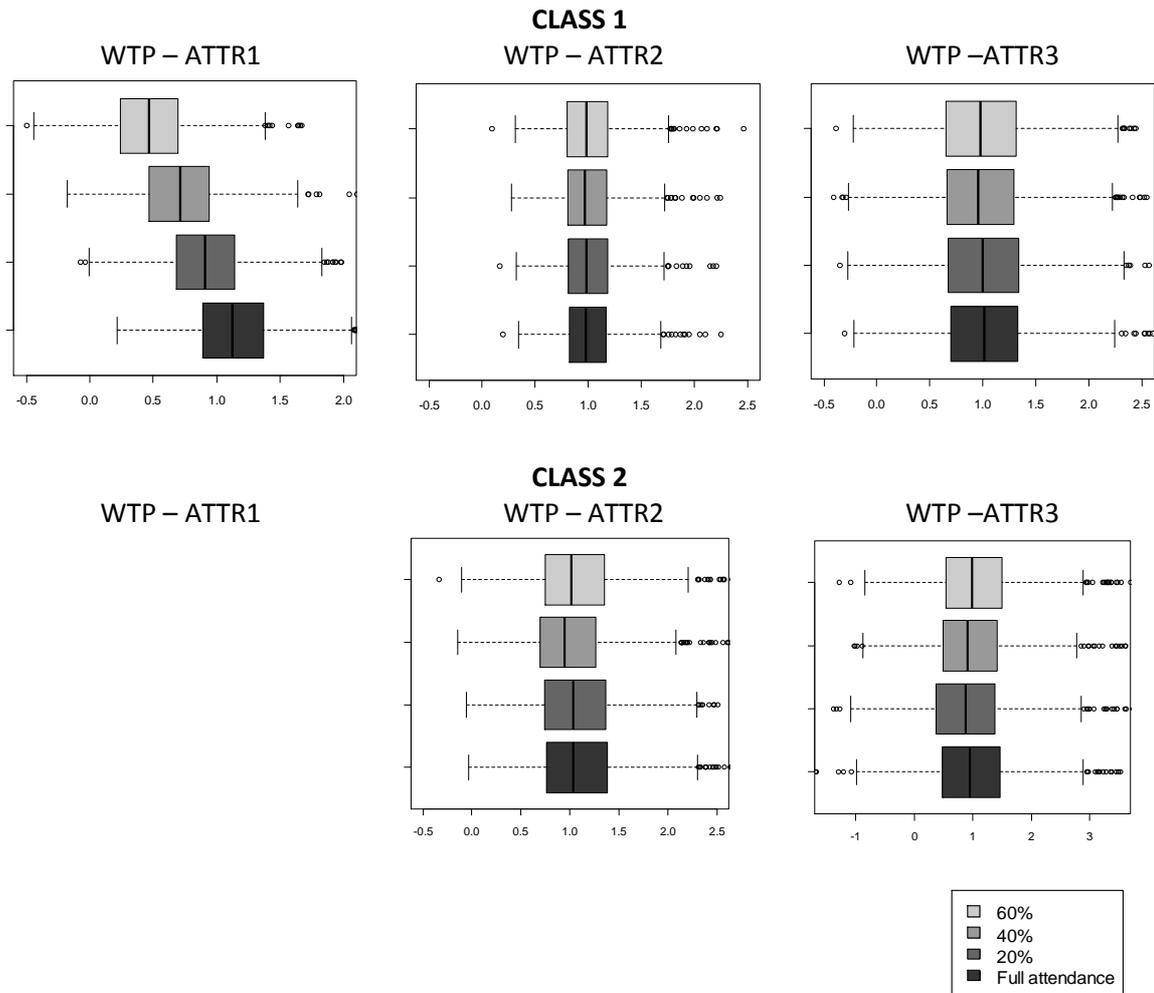
Finally, Figure 16 presents the mean probabilities of belonging to the class with the coefficient of attribute equal to zero. As shown in this figure, these probabilities are not estimated correctly.

Figure 16: ECL, ATTR1 Non-attended, Probabilities to belong to the class
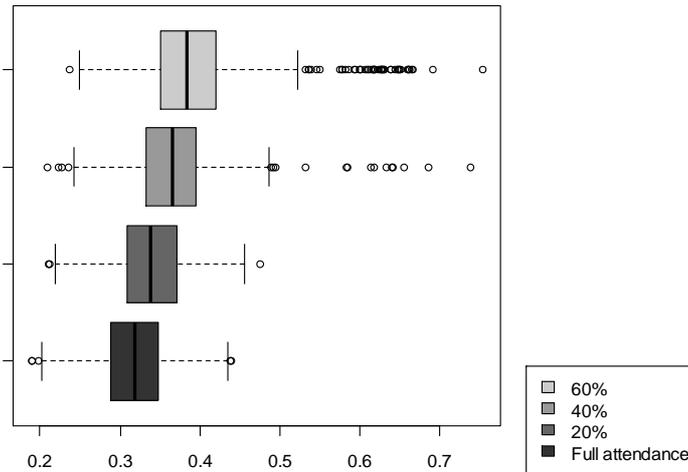
To conclude, according to our simulation experiment results, the SNA approach seems to work well in the presence of non-correlated error terms but the results with correlated errors are mixed. On the one hand, it fails to deal correctly with attribute non-attendance in the presence of correlated errors due to panel data structure but seems to work correctly when the correlation is specified among the non-SQ utility functions.

In regards to the other approach, there seems to be a serious problem of the ANA approach using a Latent Class model specification to dealing with attribute non-attendance. According to the simulations presented in this section, the ANA approach does not deal correctly with non-attended attribute in any of the two presented settings, namely including non-correlated and correlated errors. This is an interesting result given that this approach is widely used in many empirical applications.

5. Discussion and conclusions

The issue of attribute non-attendance or ignoring attributes has received increasing attention in the recent literature on DCE. The literature review shows that non-attendance takes place in DCE. It is indeed an important issue in terms of the reliability of this valuation technique for three main reasons: first, because from a behavioural point of view individuals are assumed to comply with compensatory behaviour; second, because from a theoretical perspective it challenges the continuity axiom of the neoclassical theory; and thirdly, because it may provoke biased welfare measures.

In order to cope with this anomaly, some authors have proposed different strategies for identifying and incorporating attribute non-attendance in the analysis of DCE. These strategies can be broadly divided into SNA and ANA approaches. In the former, researchers use follow-up questions in order to identify non-attended attributes, while in the latter researchers analyse the consistency of respondents' actual choices. However, so far it is not clear which treatment offers better results in terms of unbiased welfare measures.

In this paper, a typical DCE was simulated in order to compare the strengths and weaknesses of the SNA and ANA approach to dealing with attribute non-attendance in DCE. The simulation results indicate that the treatments so far proposed are not in all cases suitable. In the absence of correlated errors, the SNA approach seems to provide with unbiased welfare estimates but the ANA approach fails to do so. On the other hand, in the presence of correlated errors, none of the approaches seems to provide with unbiased WTP estimates in all cases.

These preliminary results allow us to extract some conclusions. In the first place, according to our results, the model performance of the SNA approach is superior to the ANA approach. This result can in fact be gathered as an intuitive one because it relies on the individuals' stated non-attendance, while the ANA approach is rather sceptical about what people say and it prefers to let the data show what attributes people did not attend. In fact, the ANA approach is not only failing to provide with unbiased welfare estimates but it seems to mistrust the reliability of stated preferences. On the other hand, more research is still needed in order to understand why the SNA approach does not seem to work with a panel data structure, which is mostly used in the estimation of discrete choice models.

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