Protest Attitudes and Stated Preferences: Evidence on Scale Usage Heterogeneity

Maria A. Cunha-e-Sá,[a] Luis C. Nunes,[a]
Vladimir Otrachshenko[b,c,*]

[a]Nova School of Business and Economics, Lisbon, Portugal

[b]Fondazione Eni Enrico Mattei (FEEM), Venice, Italy

[c] Euro-Mediterranean Center on Climate Change (CMCC), Lecca, Italy

Abstract

We contribute to the stated preference literature by addressing scale usage heterogeneity regarding how individuals answer attitudinal questions capturing lack of trust in institutions and fairness issues. Using a latent class model, we conduct a contingent valuation study to elicit the willingness-to-pay to preserve a recreational site. We find evidence that respondents within the same class, that is, with similar preferences and attitudes, interpret the Likert scale differently when answering the attitudinal questions. We identify different patterns of scale usage heterogeneity within and across classes and associate them with individual characteristics. Our approach contributes to a better understanding of individual behavior in the presence of protest attitudes.

Keywords: Scale usage heterogeneity; Likert scale; protest attitudes; contingent valuation; latent class model.

JEL Classification Numbers: C35, Q51

*Corresponding author: Vladimir Otrachshenko; Address: Fondazione Eni Enrico Mattei, Isola di S. Giorgio Maggiore, 30124, Venice, Italy. Email: vladotr@novasbe.pt

1 Introduction

Survey based techniques, such as Contingent Valuation (CV) and Choice Modelling, have been widely used in many research fields, namely, economics, sociology, and political science, to elicit the willingness-to-pay (WTP) for non-market goods. These techniques rely on the neoclassical theory of preferences assuming that individuals behave rationally. However, elicited preferences are also affected by other individual factors.[1] Different individuals may have different WTPs, not only because they differ in terms of preferences, but also in their beliefs or attitudes. A typical situation is when respondents state zero values to open-ended questions or refuse to accept any CV bids, even though they may value the good in question.[2] This behavior is frequently attributed to protest attitudes associated with the lack of trust in institutions, fairness issues, strategic acting, or respondents' disagreement with some part of the survey.[3] As a result, the elicited WTP obtained from the use of standard SP techniques may not represent the "true" one if protest attitudes are ignored.

Latent Class Models (LCM) have been used in the literature to identify distinct groups of people with different preferences, beliefs, or attitudes, where the individual class membership is unknown or latent. In this context, recent valuation studies include a set of follow-up questions in their surveys, representing an important source of additional information regarding individual attitudes. In general, attitudinal questions involve a discrete rating scale, such as the Likert scale. In particular, the 5-point Likert scale (from "strongly disagree" to "strongly agree") is often used. However, even individuals with similar prefer-

[1] For instance, Brown and Taylor [8] discuss gender differences regarding hypothetical bias. Another example is Botzen and van der Bergh [6] on individual risk attitudes related to climate change. For a general discussion see Bateman *et al.*[2].

[2] See Carson and Groves [10], Mitchell and Carson [19], among others.

[3] See Mitchell and Carson [19], Blamey [5], Meyerhoff and Liebe [17] and [18], Polomé [20], among others.

ences and attitudes may interpret and use the same scale ratings (categories) differently. For instance, some people answer only in the middle of the scale, while others may use the lower or upper end on the Likert scale. This phenomenon is known as scale usage heterogeneity and has been discussed in the context of consumer behavior literature by Rossi *et al.* [22], Wong *et al.* [23], and Jong *et al.* [15], among others.

This paper contributes to the CV literature by addressing scale use heterogeneity in the context of latent class analysis. We identify the factors that may explain why respondents use the scale differently, namely, by associating their answers with socioeconomic and preference variables.

The results are discussed in the context of a CV study regarding the preservation of a recreation site in the north of Portugal. After the standard CV question in the questionnaire, a set of attitudinal questions related to the budget issues and protest attitudes associated with the lack of trust in institutions and fairness issues is included.

The estimation results suggest three classes that differ with respect to the degree of protest attitudes as well as to the willingness-to-pay. We find evidence of the presence of scale usage heterogeneity, varying across classes, which is not related to WTP. Scale usage heterogeneity can also be associated with individual characteristics. For instance, respondents that visited the site more than once and belong to the classes that value the good use the upper end of the scale when answering the institutional attitudinal questions. Therefore, independently of being protestors or not, those that have visited the site more than once are more concerned with its preservation, and, hence, with the quality of the institutions that are responsible for it. Besides, among those that have higher protest attitudes, respondents that are employed and have visited the site more than once state the higher value when responding to institutional questions. Hence, these respondents are more critical with respect to the quality of institutions, sug-

gesting that misuse of fiscal revenue is an especially sensitive issue for employed individuals. Finally, we find evidence of justification bias, that is, the response to the CV question affects the way people answer attitudinal questions.[4]

The remainder of the paper is organized as follows. The next section presents the theoretical methodology. Section 3 describes the data. Then, Section 4 presents and discusses the estimation results, while Section 5 concludes the paper. Tables and Figures are presented in the Appendix.

2 The Model

In this section we describe the proposed statistical methodology to estimate the underlying WTP for non-market-goods when using CV and attitudinal data. Our model is based on the LCM as described in McLachlan and Peel [16]. Individuals are assumed to belong to one of several classes that differ in terms of the underlying WTP as well as unobserved behavioral, psychological, or attitudinal aspects. Even though individual class membership is not directly observed by the researcher, it can be inferred from the responses to the attitudinal and CV questions.

An important feature of our model is that it takes into account possible individual scale usage heterogeneity in the responses to the attitudinal questions. This unobservable heterogeneity is captured by a latent variable, designated as subjective scaling variable.[5] As shown below, our model also allows to test for testing heterogeneity associated or not with the underlying WTP.

The general representation of the model is illustrated in Figure 1. Rectangles represent observed variables and ellipses represent unobserved variables, such as WTP, latent class, and subjective scaling. This approach is similar to

[4] This bias is widely discussed in different economic fields, such as health, labor, transportation, and environment. See Au *et al.* [1], Bound [7], Ben-Akiva *et al.* [3], Cunha-e-Sá *et al.* [11], among others.

[5] See Bollen [4] for a discussion on latent variable models.

that of Ben-Akiva *et al.* [3], Provencher *et al.* [21], Cunha-e-Sá *et al.* [11]. The only difference is that in this model we introduce the subjective scaling variable affecting the responses to the CV and the attitudinal questions. The solid lines represent the CV model, where the CV question depends on the bid and underlying WTP. The subjective scaling is allowed to be the class specific. This relationship is presented by the dotted line from the latent class variable to the scaling variable. In addition, we explore the correlation between explanatory variables and subjective scaling, which is highlighted by the dashed-dotted arrows from the explanatory variables to the subjective scaling variable. Following Cunha-e-Sá *et al.* [11], the dashed arrows from the CV response to the attitudinal questions represent justification bias.

In order to estimate the willingness-to-pay, we follow the random WTP approach as described in Bateman *et al.* [2], and Haab and McConnell [13]. The WTP for an individual n in class c can be written as follows:

$$\mathbf{WTP}_n^c = \mathbf{V}(\mathbf{Z}_n, \mathbf{S}_n^*, \boldsymbol{\vartheta}_n^c; \boldsymbol{\alpha}^c) \tag{1}$$

where $\mathbf{Z}_n$ is a $k \times 1$ vector of explanatory variables that reflects individual-specific socioeconomic characteristics, $\mathbf{S}_n^*$ is the subjective scaling variable, $\boldsymbol{\vartheta}_n^c$ is a stochastic component capturing other unobservable individual heterogeneity, and $\boldsymbol{\alpha}^c$ vectors of parameters for each class $c = 1, ..., C$. Assuming a log-linear model we have that, conditional on an individual n belonging to class c , $\ln(\mathbf{WTP}_n^c)$ can be written as follows:

$$\ln(\mathbf{WTP}_n^c) = \boldsymbol{\alpha}_1^c \mathbf{Z}_n + \boldsymbol{\alpha}_2^c \mathbf{S}_n^* + \boldsymbol{\vartheta}_n^c \tag{2}$$

In our application we adopt the usual logit model and assume that $\boldsymbol{\vartheta}_n^c/\sigma^c$ follows a logistic distribution where σ^c is a scale parameter affecting the variance of the stochastic term in class c such that the cumulative distribution function of $z \equiv \boldsymbol{\vartheta}_n^c/\sigma^c$ is given by $\mathbf{F}(\mathbf{z}) = e^{\mathbf{z}}/(1 + e^{\mathbf{z}})$.

In our application the dichotomous choice referendum was chosen as the format of the CV question. It follows that an individual responds to the CV question with "Pay" or "Not Pay" if his WTP is "larger" or "not larger" than the proposed bid amount, respectively. Defining $\mathbf{u}_n = 1$ when the response is "Pay", and $\mathbf{u}_n = 0$ when it is "Not Pay", we have that:

$$\mathbf{u}_n = \begin{cases} 1 & \text{if } \mathbf{WTP}_n^c > \text{Bid}_n \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where Bid_n is the randomly proposed bid amount. Thus, the probability that an individual n belonging to class c chooses to pay is given by:

$$\mathbf{P}_u(\mathbf{u}_n = \mathbf{1} | \mathbf{Z}_n, \mathbf{S}_n^*, \text{Bid}_n, c) = \mathbf{F}(\boldsymbol{\beta}_1^c \mathbf{Z}_n + \boldsymbol{\beta}_2^c \mathbf{S}_n^* + \boldsymbol{\beta}_3^c \ln(\text{Bid}_n)) \tag{4}$$

where $\beta_1^c = \boldsymbol{\alpha}_1^c / \sigma^c$, $\beta_2^c = \boldsymbol{\alpha}_2^c / \sigma^c$ and $\beta_3^c = -\mathbf{1}/\sigma^c$. The median WTP in class c is given by $\text{Med}(\mathbf{WTP}_n^c) = \exp\left\{ -\frac{\boldsymbol{\beta}_1^c \mathbf{Z}_n + \boldsymbol{\beta}_2^c \mathbf{S}_n^*}{\beta_3^c} \right\}$.

The responses to the attitudinal questions are categorically ordered and are measured in a Likert scale taking values from 1 to T. These responses are denoted by a $(p \times 1)$ vector $\mathbf{I}_n = (\text{I}_{n1,...,}\text{I}_{nJ})'$. Each response j of an individual n can be represented as follows:

$$\mathbf{I}_{nj} = \begin{cases} \mathbf{T}_j \; if \;\; \boldsymbol{\tau}_{j,T_j-1}^c < \text{I}_{nj}^* \\ \mathbf{T}_j - 1 \; if \;\; \boldsymbol{\tau}_{j,T_j-2}^c < \text{I}_{nj}^* < \boldsymbol{\tau}_{j,T_j-1}^c \\ \qquad . \\ \qquad . \\ \qquad . \\ 2 \quad if \;\; \boldsymbol{\tau}_{j,1}^c < \text{I}_{nj}^* < \boldsymbol{\tau}_{j,2}^c \\ 1 \quad if \;\; \text{I}_{nj}^* < \boldsymbol{\tau}_{j,1}^c \end{cases} \tag{5}$$

where $\boldsymbol{\tau}_{j,k}^c$ represents the threshold of switching from category $k-1$ to category k when an individual belongs to class c, and $\mathbf{I}_{nj}^*$ represents the corresponding latent unobserved response. We denote by $\boldsymbol{\tau}$ the vector of all $\boldsymbol{\tau}_{j,k}^c$, $j = 1, ..., p, k = 1, ..., T-1$.

The responses to the attitudinal questions are denoted by a $p \times 1$ vector $\mathbf{I}_n^*$, and are assumed to depend on the class c, the response to the CV, $\mathbf{u}_n$, and the

subjective scaling $\mathbf{S}_n^*$ according to:

$$\mathbf{I}_n^* = \mathbf{\Theta}^c + \Psi^c \mathbf{u}_n + \Lambda^c \mathbf{S}_n^* + \boldsymbol{\varepsilon}_n^c \tag{6}$$

where $\mathbf{\Theta}^c$ and Ψ^c are $p \times 1$ vectors of parameters and Λ^c is a $p \times m$ vector of factor loadings for class c, respectively, and $\boldsymbol{\varepsilon}_n^c$ is a $p \times 1$ vector of measurement errors that follow a distribution $D(0, \Sigma_\varepsilon^c)$. In our application we use a logistic distribution.

If all the elements of the vector of factor loadings Λ^c are equal to zero in a given class c, then the model assumes that every individual in that class interprets the Likert scale similarly when responding to all the attitudinal questions. On the other hand, if some of the elements of Λ^c are statistically different from zero, it means that the individuals in that class interpret the Likert scale differently and, as a result, may provide different responses. Moreover, this model allows us to test if this scale usage heterogeneity in a given class is associated or not with different WTPs by checking the significance of $\boldsymbol{\beta}_2^c$ in equation (4). If $\boldsymbol{\beta}_2^c$ turns out not to be significant, it means that although the individuals in class c may provide different responses to some of the attitudinal questions, they may still be considered as homogeneous in terms of the underlying WTP distribution.

From equations (5) and (6) we derive the probability of individual n answering $\mathbf{I}_n$ conditional on belonging to a particular class c, having responded $\mathbf{u}_n$, and the subjective scaling $\mathbf{S}_n^*$, which is denoted as $\mathbf{g}_I(\mathbf{I}_n|\mathbf{u}_n, \mathbf{S}_n^*, c)$. The observed explanatory variables, $\mathbf{Z}_n$, may also affect the subjective scaling $\mathbf{S}_n^*$. Thus, the structural equation for this relationship is described by

$$\mathbf{S}_n^* = \mathbf{\Phi}^c \mathbf{Z}_n + \boldsymbol{\xi}_n^c \tag{7}$$

where $\mathbf{\Phi}^c$ is a $m \times l$ coefficient matrix, and $\xi_n^c \sim D(0, \Sigma_\xi^c)$ is a $m \times 1$ vector of $i.i.d.$ random variables for each class c.

The combination of equations (4) and (7) gives the probability that an individual n belongs to class c conditional on responses to $\mathbf{I_n}, \mathbf{u}_n$, explanatory variables $\mathbf{Z}_n$, and subjective scaling $\mathbf{S}_n^*$ is:

$$\mathbf{P}(\mathbf{c_n} = \mathbf{c}|\mathbf{I_n}, \mathbf{u}_n, \mathbf{Z}_n, \mathbf{S}_n^*, \mathrm{Bid}_n; \boldsymbol{\theta}) = \frac{\mathbf{P}(c_n = c)\mathbf{P}(u_n = i|\mathbf{Z}_n, \mathbf{S}_n^*, \mathrm{Bid}_n, c)\mathbf{g}_I(\mathbf{I}_n|\mathbf{u}_n, \mathbf{S}_n^*, c)}{\sum_{c=1}^{C} \mathbf{P}(c_n = c) \times \mathbf{P}(u_n = i|\mathbf{Z}_n, \mathbf{S}_n^*, \mathrm{Bid}_n, c)\mathbf{g}_I(\mathbf{I}_n|, \mathbf{u}_n, \mathbf{S}_n^*, c)} \tag{8}$$

The joint probability of the responses to the CV and attitudinal questions, conditional on the exogenous explanatory variables, $\mathbf{Z}_n$ and Bid_n is given by

$$\mathbf{f}(\mathbf{I_n}, \mathbf{u}_n|\mathbf{Z}_n, \mathrm{Bid}_n, \boldsymbol{\theta}) = \sum_{c=1}^{C} \int_{S^*} \prod_{i=1,2} \mathbf{1}(\mathbf{u}_n = \mathbf{i})\mathbf{P}_u(\mathbf{u}_n = \mathbf{i}|\mathbf{Z}_n, \mathbf{S}_n^*; \boldsymbol{\beta}^c, \boldsymbol{\sigma}^c) \times \tag{9}$$

$$\times \mathbf{P}(c_n = c)\mathbf{g}_I(\mathbf{I}_n\ |\mathbf{u}_n, \mathbf{S}_n^*; \boldsymbol{\sigma}^c, \boldsymbol{\Lambda}^c, \boldsymbol{\Sigma}_\varepsilon^c)\mathbf{g}_{S^*}(\mathbf{S}_n^*\ |\boldsymbol{\Phi}^c, \boldsymbol{\Psi}^c, \boldsymbol{\Sigma}_\xi^c)\mathbf{d}\mathbf{S}_n^*$$

where $\mathbf{1}(.)$ is the indicator function, $\mathbf{P}_u$ is the probability that an individual n pays ($\mathbf{u}_n = \mathbf{1}$) or does not pay ($\mathbf{u}_n = \mathbf{0}$), given by (4), $\mathbf{g}_I$ is the probability density function of the observed responses to attitudinal questions obtained by equations (5) and (6), $\mathbf{g}_{S^*}$ is the probability density function of the subjective scaling derived from equation (7), and

$$\boldsymbol{\theta} = \left\{(\boldsymbol{\beta}_1^c, \boldsymbol{\beta}_\mathbf{2}^\mathbf{c}, \boldsymbol{\beta}_\mathbf{3}^\mathbf{c}, \boldsymbol{\Lambda}^c, \boldsymbol{\Phi}^c, \boldsymbol{\Psi}^c, \boldsymbol{\Sigma}_\varepsilon^c, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}, \boldsymbol{\Sigma}_{\boldsymbol{\xi}}, \boldsymbol{\tau}^\mathbf{c}, \boldsymbol{\sigma}^c, \delta^c, \boldsymbol{\gamma}^c), c = 1, 2, ..., C\right\} \tag{10}$$

is a vector of the parameters of the model. The integration takes place over the subjective scaling $\mathbf{S}^*$.

Finally, the maximum likelihood estimator can be obtained by

$$\max_\theta \mathbf{L}(\boldsymbol{\theta}) = \max_\theta \left(\prod_{\mathbf{n=1}}^{\mathbf{N}} \mathbf{f}(\mathbf{I_n}, \mathbf{u_n}|\mathbf{Z_n}, \mathrm{Bid}_\mathbf{n}, \boldsymbol{\theta})\right) \tag{11}$$

where N denotes the number of individuals in the sample.

3 Case Study

The data for the empirical application were collected in the summer of 2006, in the Alto Douro Wine Region located in the north of Portugal, to the east of the city of Oporto, in the north of Portugal. The Alto Douro Wine Region became part of UNESCO's World Heritage cultural landscape in 2001. This landscape is comparable to the rice-growing terraces of Banaue in the Philippines. This site is one of the oldest historical winemaking regions in the world, where the famous Port Wine is produced. However, in the last three decades the old vineyards have indergone transformation in order to decrease costs and increase production efficiency. This transformation causes the destruction of the original landscape.

To preserve the unique landscape of this region, which is an important recreation site, the winegrowers have to be compensated for the incurred cost. To evaluate the benefits from the preservation of the traditional attributes of the vineyard landscape in the Douro Valley, an onsite face-to-face survey of a random sample of visitors to the site was conducted. The money raised would go to a public institution that would compensate winegrowers for the incurred costs of keeping the traditional landscape. The payment mechanism that was proposed to respondents was an annual payment that would be collected in addition to the annual income tax.

In order to evaluate the willingness-to-pay for the landscape preservation, the questionnaire included a CV question in the form of referendum dichotomous choice. Each respondent was asked a CV question about an improvement in the level of preservation. The status-quo is the case of no preservation, and the bids vary among the respondents. After the CV question the respondents were asked several attitudinal questions related to the budget constraint (B1-B4) associated with rational behavior, the quality of institutions (I1-I4), and fairness issues (F1-

F3), representing protesting behavior (see Appendix for details). All attitudinal questions were measured on a 5-point Likert scale (from strongly disagree (1) to strongly agree (5)). As for some categories there were few responses, they were merged with the adjacent ones.

The sample used in this paper has 706 observations. Table 1 provides descriptive statistics for all the variables used in the estimations. In Table 2, the distribution of responses to the attitudinal questions with merged categories is presented. As can be seen from this table, many respondents answered 3 and 4 on a Likert scale, meaning that they agreed or strongly agreed with the corresponding statements.

4 Estimation Results

In order to identify the optimal number of classes for the model, we use five information criteria, namely AIC, BIC, ABIC, AICC, and CAIC. As seen in Table 3, the majority are in favor of the model with three classes. The results for this model are shown in Table 4. The first section of Table 4 corresponds to equation (6) where the factor loadings are presented. The next section corresponds to equation (7) where the relationship between the subjective scaling and socioeconomic and preference variables is explored. In the third section we present the results for the CV equation (4),and in the fourth the justification bias is presented. Finally, the last section shows the median WTP, the confidence interval for WTP, the number of parameters, probability of belonging to each class, and entropy.

We start by characterizing each class based on the corresponding estimated parameters. The estimation results of the CV equation (4) are presented in the third section of Table 4. The significant estimates of ln(Bid) in classes 1 and 2 suggest that individuals in these classes value the good. We note that the

difference found in the estimated WTPs is not negligible, and can be attributed to the different protest attitudes of individuals in those classes. In contrast to the other two classes, in class 3 ln(Bid) is not significant, suggesting that individuals in this class do not value the good.

Following Cunha-e-Sá *et al.* [11], we allow individuals to justify the response to the CV question when responding to the set of attitudinal questions. This behavior is known as justification bias. The estimated coefficients for the budget constraint issues and justification biases with respect to the lack of trust in institutions and fairness issues are presented in the second section of Table 4. The estimates on institutional (I2-I4) issues are significant in class 1. When individuals refuse to pay because the bid is above their WTP it may be the case that they try to justify their negative CV response by looking like a protestor. Also, the individuals in classes 1 and 2 use the budget constraint attitudinal questions to justify the "Not Pay" CV answer by inflating the responses to those questions, representing rational behavior. Therefore, we may conclude that justification biases with respect to institutions and fairness issues are a sensitive issue for those individuals.

The presence of justification implies that the probability distributions of the responses to some of the attitudinal questions are shifted to the right for the "Not Pay" answers compared to the "Pay" ones, as can be observed when comparing the results in Tables 5A to 5B, respectively. In both tables we observe that the distributions of the responses to questions I1-I4 and F1-F3 for class 2 are shifted to the right relative to those in class 1, underlscoring the importance of the lack of trust in institutions and fairness issues for respondents in class 2. Therefore, we conclude that class 1 represents individuals with low protest attitudes (non-protestors), while class 2 represents those with high protest attitudes (protestors).

Regarding rational behavior captured by the responses to the questions (B1-

B4) in Table 5A, we find that the modes of the distributions in classes 1 and 2 are mostly disagree and strongly disagree (B1, B3, and B4), respectively. Comparing these classes with respect to the institutional and fairness issues for "Pay" responses, we find that the mode in class 1 is either indifferent (I2 and I3) or agree (I1 and I4), while in class 2 the mode is either agree (I2 and I3) or strongly agree (I1 and I4). Concerning the fairness issues, in class 1, the mode ranges from disagree to agree, while in class 2 the mode is between strongly disagree and strongly agree (F1, F3, and F2, respectively).

Based on these results, we conclude that individuals in class 1 have lower protest attitudes compared to individuals in class 2. Therefore, the calculated median WTP (34.12 Euros) in class 1 is expected to be closer to the "true" one. Nevertheless, the individuals in class 2 that have a higher protest attitude are also willing to pay some positive amount even though the estimated median WTP (8.29 Euros) is substantially lower than in class 1.

4.1 Scale Usage Heterogeneity

We now discuss the estimation results regarding scale usage heterogeity. We first test for its presence, second, explore its causes, and third examine how the subjective scaling and socioeconomic and preferences variables affect the responses to the attitudinal questions.

Since the estimated coefficients of the subjective scaling variable are significant (first section of Table 4), the presence of scale usage heterogeneity among respondents within each class is confirmed. For instance, in class 1, the factor loadings are significant only for the institutional issues (I2-I4), while in classes 2 and 3 the factor loadings are significant for budget constraint, institutional, and fairness issues (B2, I1-I4, and F3 in class 2 and B1, B3, and I4 in class 3). Given these results, we may conclude that the subjective scaling of individuals affects the responses to some attitudinal questions, and varies across classes.

Moreover, we test whether the individual subjective scaling can be directly associated with the economic valuation of the good, in particular, if it is significant in the CV question (third section of Table 4). As observed, the estimated coefficients of this variable are not statistically significant in all classes. This means that the estimated WTP is representative of all individuals within each class, and is unrelated to the individual subjective scaling.

As stated by Rossi *et al.* [22], scale usage heterogeneity is a well documented phenomenon. However, its causes are not well understood. In our model we explore the association between the subjective scaling and individual characteristics, such as gender, employment status, and the previous visits to the site. The results are shown in the second section of Table 4. While the estimated coefficients on visit are positive and significant in classes 1 and 2, the estimated coefficient on gender is significant only in class 1. Regarding the employment status (emp), we find that the coefficients on this variable are significant in classes 2 and 3, positive and negative, respectively.

Since in non-protestor class, class 1, we find positive and significant factor loadings on the institutional issues (I2-I4), we may conclude that the individuals that previously visited the site use the higher values on the Likert scale to answer those questions. Also, when compared to males in this class, females use the lower values when responding to those questions.

In protestor class, that is, class 2, the significant positive factor loadings on I1-I4 and F3, and coefficients on visit and emp suggest that those that are employed and have previously visited the site state higher values when responding those attitudinal questions. Therefore, as taxes represent a high burden on salaries, misuse of tax revenues by public institutions is a highly sensitive issue, especially for employed citizens. At the same time, the factor loading on B2 is negative, meaning that employed respondents who previously visited the site provide lower values when responding to this attitudinal question, suggesting

that they can afford to pay for the good.

These results also show that individuals in classes 1 and 2 that have previously visited the site use the upper end of the scale when responding the institutional attitudinal questions. Therefore, independently of the degree of protesting, efficiency of institutions is an issue for those who show a preference for the valued good.

5 Conclusion

We contribute to the CV literature by addressing scale use heterogeneity in the context of LCM. Our approach enables us to better understand individual behavior when responding CV surveys that include attitudinal questions.

Our model is applied to a CV survey conducted in the Alto Douro Wine Region, Portugal, to elicit the WTP to maintain the traditional landscape in the presence of different sources of protest attitudes. We find evidence that respondents within the same class, that is, with similar preferences and attitudes, interpret the Likert scale differently when responding to the attitudinal questions. We show that grouping individuals into classes with respect to their protest attitudes as well as to the economic valuation of the good allows for identifying different patterns of scale usage heterogeneity within a given sample, thereby, highlighting the most sensitive issues for each particular group and across groups with different characteristics. This could not be captured without testing for the impact of the subjective scaling.

Finally, the methodology followed is flexible enough to be easily extended and applied to account for different behavioral and psychological attitudes. While in our application it is not possible to check how close the predicted WTP is to the actual unobserved one, it would be interesting to make this comparison in other contexts, such as when both revealed and stated preference data are

available. This is left for future research.

References

[1] Au, D., T. F. Crossley, and M. Schllhorn, "The Effect of Health Changes and Long-term Health on the Work Activity of Older Canadians", *Health Economics* **10**, 999-1018, 2005.

[2] Bateman I. , R. Day, B. Carson, M. Hanemann, N. Hanley, T. Hett, M. Jones-Lee M, G. Loomes, S. Mourato, E. Ozdemiroglu, D. Pearce, R. Sugden, and J. Swanson, "Economic valuation with stated-preference techniques", Edward Elgar, Cheltenham, 2002.

[3] Ben-Akiva, M., J. Walker, A. Bernardino, D. Gopinath, T. Morikawa, and A. Polydoropoulou, "Integration of Choice and Latent Variable Models", in (H. Mahmassani, Ed.) In Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges, Elsevier Science, 431-470, 2002.

[4] Bollen, P.M., "Structural Equations with Latent Variables", Wiley Series in Probability and Mathematical Statistics, John Wiley & Sons, 1989.

[5] Blamey, R. K.,"Decisiveness, Attitude Expression and Symbolic Responses in Contingent Valuation Surveys", *Journal of Economic Behavior & Organization*, Vol. 34, pp. 577-601, 1998.

[6] Botzen, W.J.W. and J.C.J.M. van den Bergh, "Risk attitudes to low-probability climate change risks: WTP for flood", *Journal of Economic Behavior & Organization* **82**, 151 166, 2012.

[7] Bound, J., "Self-Reported Versus Objective Measures of Health in Retirement Models", *Journal of Human Resources* **26**, 106-138, 1991.

[8] Brown, K., and L. Taylor, "Do as you say, say as you do: evidence on gender differences in actual and stated contributions to public goods", *Journal of Economic Behavior & Organization* **43,** 127-139, 2000.

[9] Carson, R., R. Mitchell, M. Hanemann, R. Kopp, S. Presser, and P. Ruud, "Contingent Valuation and Lost Passive Use: Damages from the Exxon Valdez Oil Spill", *Environmental & Resource Economics* **25**, 257-86, 2003.

[10] Carson, R., and T. Groves, "Incentive and Informational Properties of Preference Questions", *Environmental & Resource Economics* **31**, 181-210, 2007.

[11] Cunha-e-Sá, M. A., L. Madureira, L.C. Nunes, and V. Otrachshenko, "Protesting and Justifying: A Latent Class Model for Contingent Valuation with Attitudinal Data", *Environmental and Resource Economics* **52**, 531-548 , 2012.

[12] Dempster, A. P. , N. M. Laird, and D. B. Rubin, "Maximum Likelihood from Incomplete Data via the EM Algorithm", *Journal of the Royal Statistical Society, Series B*, **39:** 1-38, 1977.

[13] Haab, T., and K. McConnell, "Valuing Environmental and Natural Resources", Edward Elgar, UK, 2002.

[14] Jakobsson, K., and A. Dragun, "The Worth of a Possum: Valuing Species with the Contingent Valuation Method", *Environmental & Resource Economics* **19**: 211-227, 2001.

[15] Jong, M. G. D, J. B. E. M. Steenkamp, and J. P. Fox, "Relaxing Measurement Invariance in Cross-National Consumer Research Using a Hierarchical IRT Model", *Journal of Consumer Research,* Vol. 34, No. 2, 260-278, 2007.

[16] McLachlan, G. J., and D. Peel, "Finite Mixture Models", New York, NY: John Wiley&Sons, 2000.

[17] Meyerhoff, J., and U. Liebe, "Protest Responses in Contingent Valuation: Explaining Their Motivation", *Ecological Economics* **57**:583-594, 2006.

[18] Meyerhoff J., and U. Liebe, "Determinants of Protest Responses in Environmental Valuation: A Meta-Study", *Ecological Economics* **70**:366–374, 2010.

[19] Mitchell, R.C., and R.T. Carson, "Using Surveys to Value Public Goods: The Contingent Valuation Method", Resources for the Future, Washington, DC, 1989.

[20] Polomé, P., "Experimental Evidence on Deliberate Misrepresentation in Referendum Contingent Valuation", *Journal of Economic Behavior & Organization*, Vol. 52, pp. 387-401, 2003.

[21] Provencher B, K. Baerenklau, and R. Bishop, "A Finite Mixture Logit Model of Recreational Angling with Serially Correlated Random Utility", *American Journal of Agricultural Economics*, 844, pp. 1066–1075, 2002.

[22] Rossi P. E., Z. Gilula, and G. M Allenby, "Overcoming Scale Usage Heterogeneity: A Bayesian Hierarchical Approach", *Journal of the American Statistical Association* **96**, No. 453, 20-31, 2001.

[23] Wong, N., A. Rindfleish, and J. E. Burroughs, "Do Reverse-Worded Items Confound Measures in Cross-Cultural Consumer Research? The Case of the Material Values Scales", *Journal of Consumer Research* **30**, 2003.

Appendix:

Attitudinal Questions:

- *Budget Constraint Issues* (B1-B4):

B1. The values are too high
B2. I can't afford to pay anything right now
B3. The landscape preservation is not my problem
B4. I would rather pay more important things

- *Institutions* (I1-I4):

I1. The landscape should be preserved with the current taxes
I2. I think money will be used for other purposes
I3. This payment will not insure the preservation of the landscape
I4. I already pay enough taxes for this preservation

- *Fairness Issues* (F1-F3):

F1. The residents of the region should pay for this preservation
F2. The local authorities and tourist operators should pay for this preservation
F3. It is not fair to ask me to pay

Table 1: Descriptive Statistics

Variable	Mean	SD	Min	Max	Description
CV Answer	0.32	0.47	0	1	Answer to the CV question(1=Pay,0=Not Pay)
Bid	46.7	29.7	10	100	Bid for the CV question in Euros
Age	45.3	13.7	18	85	The age of the respondent
Emp	0.78	0.41	0	1	Employment Condition(1=Employed,0=otherwise)
Visit	0.59	0.49	0	1	(1=If respondent has visited this place before,0=otherwise)
Gender	0.47	0.25	0	1	(1=If respondent is a female, 0= respondent is a male)

Table 2: Distribution of answers to the attitudinal questions (%)

Attitudinal Questions	Adjusted Scale			
	1	2	3	4
B1[a]	27.2	17.6	37.1	18.1
B2[b]	8.9	32.6	32.2	26.3
B3[b]	25.8	54.4	7.1	12.7
B4[a]	27.9	32	32.7	7.4
I1[a]	4.2	7.1	60.9	27.8
I2[a]	11.9	28.9	41.5	17.7
I3[a]	13	31.6	38.2	17.1
I4[a]	6.1	12.3	54.4	27.2
F1[b]	21.1	50.8	13.7	14.3
F2[a]	18.4	13.7	48.6	19.3
F3[a]	16.9	15.6	52.1	15.4

Notes:

a) levels 1 and 2 in a Likert scale are merged in level 1 in the table
b) levels 4 and 5 in a Likert scale are merged in level 4 in the table

Table 3: Model selection criteria

Criteria	Number of Classes		
	2 Classes	3 Classes	4 Classes
LL	-8801	-8614	-8507
AIC	17848	17593	**17509**
BIC	**18409**	18423	18636
ABIC	18019	**17845**	17851
AICC	17900	**17720**	17776
CAIC	18075	**17928**	17965
# of parameters	123	182	247

Table 4: Estimation Results

	Class 1	Class 2	Class 3
Factor Loadings in Equation (6)			
B1	0.137 (0.73)	-0.374 (0.11)	**0.845 (0.00)**
B2	0.752 (0.22)	**-0.407 (0.03)**	1.984 (0.11)
B3	0.332 (0.20)	0.412 (0.10)	**1.586 (0.00)**
B4	0.188 (0.54)	0.249 (0.39)	0.280 (0.27)
I1	0.023 (0.91)	**0.929 (0.01)**	-0.099 (0.60)
I2	**2.141 (0.00)**	**1.105 (0.01)**	-0.168 (0.66)
I3	**1.242 (0.00)**	**2.416 (0.01)**	0.046 (0.87)
I4	**1.720 (0.04)**	**2.063 (0.02)**	**0.342 (0.06)**
F1	0.227 (0.51)	0.112 (0.79)	1.473 (0.28)
F2	-0.010 (0.97)	0.143 (0.62)	0.162 (0.44)
F3	2.808 (0.29)	**0.967 (0.02)**	0.388 (0.18)
Measurment Equation (7)			
visit	0.892 (0.00)	0.667 (0.00)	-0.074 (0.72)
gender	-0.456 (0.09)	0.222 (0.29)	0.284 (0.36)
emp	0.375 (0.13)	0.821 (0.00)	-1.321 (0.00)
CV Equation (4)			
constant	2.730 (0.01)	2.712 (0.14)	0.016 (0.99)
factor	0.281 (0.46)	-0.486 (0.44)	-0.159 (0.70)
ln(Bid)	-0.784 (0.01)	-0.963 (0.00)	-0.290 (0.36)

Notes: In parentheses are p-value WTP is in Euros
S.E. is a standard error
The standard errors for the median WTP are computed by using the delta method

Table 4 (Cont): Estimation Results

	Class 1	Class 2	Class 3
Estimated Ψ^c in Equation (6) "Justification Bias"			
B1	**-2.415 (0.09)**	**-1.438 (0.00)**	-0.943 (0.39)
B2	-2.644 (0.30)	**-1.091 (0.01)**	0.487 (0.59)
B3	**-1.854 (0.00)**	**-0.868 (0.01)**	0.042 (0.95)
B4	-2.470 (0.43)	**-1.364 (0.02)**	-0.243 (0.81)
I1	-0.686 (0.19)	0.019 (0.98)	-0.455 (0.37)
I2	**-4.321 (0.00)**	-0.846 (0.24)	0.081 (0.86)
I3	**-2.666 (0.03)**	-1.774 (0.18)	-0.555 (0.14)
I4	**-2.473 (0.03)**	-1.243 (0.25)	**-1.167 (0.01)**
F1	-0.327 (0.65)	-0.887 (0.17)	0.721 (0.42)
F2	0.366 (0.53)	0.781 (0.17)	-0.740 (0.45)
F3	-3.171 (0.34)	**-1.769 (0.02)**	**-2.078 (0.01)**
Median(WTP) / S.E.	**34.12 / 0.48**	**8.29 / 0.53**	**1.48 / 0.25**
Confidence Interval of Median(WTP)	[33.16 , 35.07]	[7.25 , 9.23]	[0.99 , 1.97]
Number of observation per Class	229	220	257
Probability	0.33	0.31	0.36
Entropy	0.78		
Number of Parameters	182		
Number of observations	706		

Notes: In parentheses are p-value WTP is in Euros
S.E. is a standard error
The standard errors for the median WTP are computed by using the delta method

Table 5A: Estimated conditional probabilities of answers to the attitudinal questions, Pay (%)

Attitudinal Questions	Class 1				Class 2				Class 3			
	1	2	3	4	1	2	3	4	1	2	3	4
B1[a]	32	50	17	1	55	7	20	18	46	16	35	3
B2[b]	1	25	70	4	33	51	9	7	1	28	34	37
B3[b]	35	59	4	2	55	36	1	8	8	77	7	8
B4[a]	31	62	7	0	69	14	11	6	25	27	45	3
I1[a]	3	13	80	4	3	2	24	71	7	9	74	10
I2[a]	21	77	2	0	11	21	42	26	10	21	61	8
I3[a]	22	70	8	0	4	18	63	15	20	35	40	5
I4[a]	3	34	63	0	4	6	31	59	8	18	67	7
F1[b]	6	63	24	7	72	21	3	4	1	60	14	25
F2[a]	9	25	63	3	14	4	17	65	28	11	57	4
F3[a]	6	52	42	0	26	19	46	9	48	22	28	2

Notes:

a) levels 1 and 2 in a Likert scale are merged in level 1 in the table

b) levels 4 and 5 in a Likert scale are merged in level 4 in the table

Table 5B: Estimated conditional probabilities of answers to the attitudinal questions, Not Pay (%)

Attitudinal Questions	Class 1				Class 2				Class 3			
	1	2	3	4	1	2	3	4	1	2	3	4
B1[a]	4	24	61	11	23	5	24	48	25	14	54	7
B2[b]	0	2	60	38	14	49	18	19	2	38	34	26
B3[b]	8	63	19	10	34	47	3	16	9	77	7	7
B4[a]	4	49	46	1	36	18	25	21	21	25	50	4
I1[a]	2	7	84	7	3	3	23	71	5	6	74	15
I2[a]	0	37	62	1	5	12	38	45	10	22	60	8
I3[a]	2	42	56	0	1	3	45	51	12	29	51	8
I4[a]	0	5	95	0	1	2	14	83	3	7	72	18
F1[b]	5	57	29	9	51	34	7	8	2	74	10	14
F2[a]	13	30	55	2	27	6	21	46	16	8	68	8
F3[a]	0	5	95	0	6	6	50	38	10	13	63	14

Notes:

a) levels 1 and 2 in a Likert scale are merged in level 1 in the table

b) levels 4 and 5 in a Likert scale are merged in level 4 in the table

Figure 1: General Representation of the Model